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Analytics in a Decision Service Context

Exploring analytical values for enhancing automated decision performance

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Abstract

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Organizations struggle to rapidly respond to competitive and changing business environments and therefore implement smarter Information Systems that incorporate automated decision services. An imminent role for complementing automated decision making are analytics, as it can evaluate past performances to provide insights on potential future decision making endeavors. While the consensus on how analytics support decision making is considerable, how analytics are utilized and the values it provide to an automated decision services is limitedly explored. Therefore the aim of this study is to examine the values that analytics provide for automated decisions services. The study followed a qualitative research approach, conducting four interviews with prominent players in the field of decision automation and decision management. The empirical data showed that analytics provides more certainty in decision making and can be used to design the initial decision services, but are more commonly used to provide insights on how the decision services can be improved. The utilization of analytics embedded in decision services, especially for predicting future outcomes based on historical data, is promptly increasing. Analytics contributes to the improvement of automated decision services, however has not been widely adapted. The study also showed that analytics performs an imperative role in decision services while at the same time continue to add value to certainty, accuracy, agility and cost reduction in a decision service context. The future perspectives of analytics in such a context include an increasing use of predictive models, to assure real-time recognition of abnormal behavior and reducing the role of subjective human thinking.

Keywords: Analytics, Decision Automation, Decision Management, Decision Services

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Index of Abbreviations

AI - Artificial Intelligence

BA - Business Analytics

BI - Business Intelligence

BOM - Business Object Model

BP - Business Process

BPMN - Business Process Model Notation

BRE - Business Rules Engine

BRMS - Business Rules Management System

BRs - Business Rules

DA - Decision Automation

DM - Decision Management

DMN - Decision Model Notation

DMS - Decision Management System

DRD - Decision Requirement Diagram

DRG - Decision Requirements Graph

IS - Information Systems

KPI - Key Performance Indicator

OLAP - Online Analytical Processing Tools

OMG - Object Management Group

SQL - Structured Query Language

UML - Unified Modelling Language

1 Introduction

1.1 Background

In an evermore competitive, fast and agility demanding world it is important for organizations to stay ahead of competitors. Strategies must constantly be changed, refined or updated to keep up with market shifts, consumer preferences or rival organizations (Taylor & Raden, 2007). According to Taylor and Raden (2007), agility is essential as it contributes to strategic alignment, which is portraying strategies in an organization's daily operations. In such a world, intelligence can be a strong foundation to limit organizational risks. Additionally, as Davenport, Harris and Morison (2009) point out, intelligence can provide insights to new business opportunities.

Information Systems (IS) are considered highly valuable tools for any competitive organization as they are able to effectively manage activities of the organization (Helo, Anussornnitisarn & Phusavat, 2008). There are various perspectives on how technology, and specifically IS, mediates organizations to change (Volkoff, Strong & Elmes, 2007). However, the implementation of IS can result in many technological difficulties such as standardization, technological complexity and compatibility problems (Helo et al., 2008). The urge for more responsive and flexible IS is part of the top priority when it comes to managing IT and information (Byrd & Turner, 2000). Improving the way how IS behave will result in a more effective organization overall (Taylor & Raden, 2007).

Managing operational decisions ensure, according to Taylor and Raden (2007), overall effectiveness of an organization. With Decision Management (DM) an organization can effectively automate operational decisions and daily operations (Taylor & Raden, 2007). Important aspects of DM are automation and analytics, which are seen as the most compelling tools to enhance decision making (Davenport, 2009). DM incorporates Decision Automation (DA) and analytics to improve agility, consistency, transparency of business decisions (Taylor & Purchase, 2016). Decision Management Systems (DMS) are not capable of learning by themselves, which means that DMS can act in the way they were originally designed for, while the macro-environment of the organization is changing. Analytics can provide insights of these changes which can play an important part in DMS design (Taylor, 2012).

It is important for organizations to make better decisions and a way for doing so is to make use of analytics (Davenport, Harris & Morison, 2009). Therefore, the focus of many organizations lies on decisions in connection to information, which is shown through the investments in Business Intelligence and other analytical information gathering technologies has increased significantly (Davenport, 2010). Accumulating better information from systems would lead to better decision making and ways of managing organizational processes

(Davenport, 2010). However, analytics do have limitations as it considers the speed of insight, transforming data into insights for the organization (Wixom, Yen & Relich, 2013).

In order for an organization to perform effectively, the operational decision making must be precise, agile, and consistent and must be executed in a fast and cost effectively manner (Taylor & Raden, 2007). With a DMS it is possible to automate operational decisions in a way to achieve the performance as mentioned above. A DMS is considered to be agile, adaptive and analytical (Taylor & Purchase, 2016). The performance of the DMS is monitored and managed to improve the decision making process (Taylor, 2013). The utilization of analytics could therefore play a valuable role in this context.

The variety of decisions causes that the fields of decision support and decision automation overlap and extend in research opportunities. The IS research field is a reference discipline and continuously evolves and innovates over time (Hosack, Hall, Paradice, & Courtney, 2012). Whereas analytics tend to be used for supporting strategic human decision making, it can also provide significant value when integrated on operational level of decision making (Elbashir, Collier & Davern, 2007). Researching analytics in an automated decision making context can aid both practitioners and academics to disclose the value of analytics in decision services.

This research is organized in the following way. First, the problem area, the research question, the purpose and the delimitations of the research are defined and proposed. The next chapter is the theoretical background of the research, which covers three important themes that are connected to the research question. The research continues with a chapter of the research method where is described how the empirical and theoretical data is collected and analyzed. The results of the analyzed data are provided and discussed accordingly. Furthermore, the contribution of these results to knowledge is covered as well. Finally, a fitting conclusion is presented.

1.2 Problem Area

As previously mentioned, decisions are an important aspect of any organization. Designing decision making in an effective manner results in an increase of performance for the overall organization (Taylor & Raden, 2007). The use of analytics can improve decision making (Selman, 2011). Taylor (2009) even claims predictive analytics integrated in automated decision making is highly valuable. This is because the action generated by the decision is likely to reflect on possible future outcomes. Analytics could therefore play an important role in a DMS.

Although organizational decisions and analytics are profound research areas (Taylor, 2009; Davenport, 2010; Davenport, Harris & Morison, 2010), there is limited empirical research that shows the effects and values of analytics in automated decision services and how these combined concepts are applied in practice. Research in this area is therefore needed, as it could bridge the gap between theory and practice as well to provide new insights of these two concepts in relation to each other.

1.3 Research Question

For the research it is interesting to investigate the use and role of analytics for the design and maintenance of decision services, and how analytics contributes to add value in automated decision services. Therefore the research is aimed to answer the following question:

What values, if any, do analytics provide for decision services?

1.4 Purpose

The purpose of this thesis is to explain the values of analytics for a decision service. The focus will be on the relationship between Decision Management, Decision Automation and Analytics, in order to get an understanding of values from analytics in a decision service context.

The answer to the research question will be explained based on the empirical findings and will be presented as a numeration of distinctive values. The research will be conducted with participants of organizations that either work or implement decision automation on a daily basis and the research tends to focus on operational decisions.

This research may contribute to the IS body of knowledge, due to the lack of empirical data in the field of analytical values for decision services. Also, the research may expose future trends in the field of analytics in connection to decision services.

1.5 Delimitations

The automation of decisions and analytics are broad research areas. This research will therefore focus on how analytics provide value for decision services, which narrows the research down to this specific part of decision automation. This research will not analyze the technical details on how to implement analytics in automated decision making.

DA is mostly utilized on an operational level and within a DM context, therefore this research study will focus on the use of analytics for automated decision services in a DM context. The use of analytics for decision making on a tactical or strategic level is utilized in a different manner and will not be covered in this research.

2 Theoretical Review

The theoretical review themes are based upon the subject of the research areas Analytics and Decision Automation, which are consequently used as themes for the theoretical review and throughout the research thesis. In order to better grasp understanding of the research context, another theme called Decision Management is supplementing the previously mentioned themes. Together, the three themes form the fundamental basics for understanding the context of the research question.

2.1 Decision Management

A way for organizations to determine how to conduct their business, is with decisions. Whether a decision is on a strategic, tactical or operational level, a decision is the core of any organization, because it determines the way an organization acts (Taylor & Purchase, 2016). Decision Management is an approach, which according to the Decision Management Manifesto (Taylor, 2013), is used for an improvement in control, automation and management of operational decisions. The Decision Management Manifesto, which introduces important principles, is developed to assist organizations that want to use DM. The Manifesto states a key role for the use of Business Rules (BRs), analytics and optimization tools in DM (Taylor, 2013).

Taylor and Purchase (2016) state that decisions could be about accepting a customer, providing a loan to a customer, rejecting a claim, managing inventory or opening a new store and that every organization encounters decision making on a daily basis in one way or another. An increasingly important component in many successful organizational business strategies is therefore understanding, managing and automating decisions and by doing so, an organization increases its overall effectiveness as well as improves their business outcomes (Taylor & Purchase, 2016).

2.1.1 Decisions

Decisions should come first in DM, which according to the Decision Management Manifesto (Taylor, 2013), means that decisions should be expressly identified, modelled and related to an organization's architecture, before concentrating on the implementation of the automated decision. The Manifesto states that the aforementioned plan is better than handling decisions secondly by deducing decisions from, e.g. BRs (Taylor, 2013). The Object Management Group (OMG) is a non-profit organization that sets standards in the field of technology (Object Management Group, 2017).

According to the Object Management Group (2016) a decision can be defined as follows:

"*The act of determining an output value from a number of input values, using decision logic defining how the output is determined from the inputs.*" (Object Management Group, 2016, p.174)

As stated in the definition, a decision transforms an input into an output based on a single or various criteria (Taylor & Purchase, 2016), which are also known as the logic of the decision (Object Management Group, 2016). Taylor and Purchase (2016) state that a decision consists of three components. The first component they mention is the input value of a decision. These input values are used for making a decision based on the logic, which the authors present as the second component of the decision. The logic consists of an expression of business knowledge (Object Management Group, 2016) or calculation and results in a specific output (Taylor & Purchase, 2016). This specific output is the third component of a decision and defined as the conclusion of the decision (Taylor & Purchase, 2016).

Not all decisions are equal or have the same impact (Fish, 2012). Fish (2012) broadly classifies decisions in two categories: high-value and low-value decisions. High-value decisions are described by him as typically strategical decisions, these decisions are made by the higher end of the hierarchy and are characterized by significant influence on the organization and infrequent execution. Low-value decision, on the other hand, are known as operational decisions, which he explains have, when solely executed, a small impact on the organization and are characterized as frequent and influence how a business performs on a daily basis (Taylor & Purchase, 2016; Fish, 2012).

Taylor (2013) points out in the Manifesto that organizations who adapt the DM approach need to fulfill four conditions for decisions in order to be appropriate. He states that decisions should be *repeatable*, basically that an organization makes these decisions on a regular basis. The second condition of the decision is being *action oriented*, with which he states that it is essential to select a feasible action as outcome. The third condition he describes is that a decision should be *non-trivial*, which means that these kind of decisions should be significant for an organization, relatable to several rules and policies, often changeable and involving a large amount of data. The final characteristic he states is that a decision should have a value for the business that is *measurable*. In the next section, DM will be further addressed as well as what will the use of this approach offer to organizations.

2.1.2 Decision Management in Context

DM, also referred to as Enterprise Decision Management (Taylor & Raden, 2007), is defined by the Manifesto (Taylor, 2013) as an approach that increases the performance of daily organizational operations (Von Halle & Goldberg, 2006). DM uses innovative and rapidly growing technologies (e.g. business rules, business processes and analytics) that result in an increase of organization's adaptability, agility (Taylor, 2013; Taylor & Purchase, 2016) and eventually the profitability of business decisions (Fish, 2012). DM is an approach that centers on automating operational decisions that will drive the business. DM focusses on operational decisions, because operational level processes are profoundly decision centered instead of system or process centered (Taylor & Raden, 2007; Taylor, 2013). According to Taylor and Purchase (2016), the urge for organizations to rapidly respond to changing business environments and the struggle to cope with more extensive data are solid reasons for organizations to automate such operational decision making.

According to Taylor and Raden (2007), the management part in the DM context consists of supervising and controlling the use of a mechanism to accomplish an end. This to ensure maintenance and improving decisions to be able to cope with real-time changing environments (Taylor & Raden, 2007). Decisions, and the logic behind the decisions can, according to Taylor (2015), not be determined once and the logic is expected to deal with several changing factors. The author states that management of these decisions concerns to making sure how to deal with changing factors and how to act on it accordingly. Taylor (2015) also argues that by monitoring decision performance, the decision making can be systematically enhanced when the outcomes do not perform as intended. Taylor and Raden (2007) consider DM to be essential and states that the use of the DM approach is required because of the following reasons:

- Decision Management is about isolating logic behind the decision and therefore separating it from business processes. Without this connection, the decision logic, as a separate part, is more manageable and can be reused within different operational environments.
- Decision Management applies analytics to make better and more precise decisions. The captured data is used to assure more informed decisions.
- Decision Management also makes it easier for organizations to improve decisions over time as the organization can focus on specific decisions. Improvement in the decision will result in improvement of all applications that use these decisions.

Operational decision making should be seen as a business asset and should be measured, controlled and improved in order for an organization to effectively perform (Taylor & Raden, 2007). The use of DM helps to be effective and offers beneficial values to automated operational decisions in five levels as stated by Fish (2012) but also Taylor and Purchase (2016):

1. Accuracy, effectiveness of the decision and analytics for data driven decisions.
2. Consistency, implementing policies for different channels and integrating decisions within the entire organization.
3. Agility, rapid response to opportunities and able to change decision strategies.
4. Latency, reducing time for decision making and the paste of executing decisions.
5. Cost, reducing cost by more automation and overall efficiency of the decision making.

The five benefits of DM are results of the competences of an organization to generate the knowledge required for making a decision and to capture this knowledge into a Decision Management System, which is able to automate these decisions with decision services (Fish, 2012). As mentioned in section *2.1.1 Decisions*, there is a clear distinction between high value strategic decisions and low value operational decisions. As strategic decisions rarely happen twice and depend on a lot of different factors, it is unlikely for organizations to automate these kind of decisions (Taylor & Raden, 2007). Taylor and Purchase (2016) state that the intended value of DM is therefore directed to the automation of operational decisions.

Taylor and Purchase (2016) present that in order for an organization to adapt DM and benefit from its values, it is needless to say that decision modelling is required. Decision modelling helps to design and specify decisions, which they explain is important for an organization's potential to manage decisions. This is similar with a Decision Management System (DMS) in which modelled decisions may be automated and analysis of data may lead to improvement of decisions (Taylor & Purchase 2016).

The use of a DMS will help the organization to encapsulate the decision services of frequently occurring operational decisions (Taylor, 2015). Taylor (2015) also points out that decision modelling helps to specify the requirements and the logic of a decision, which is needed in order to translate a decision into a decision service. The performance of the decision service, together with the impact on the organization is tracked and analytics are used to improve decisions (Taylor, 2015).

2.1.3 Decision Management System

Organizations who adapt DM are likely to automate decisions which are best be managed and attained by developing a Decision Management System (DMS) (Taylor & Purchase, 2016). The use of DMS has helped organizations to attain a better performance (Taylor, 2011), which is related to the characteristics of being adaptive, agile and analytical (Taylor & Purchase, 2016).

Taylor and Purchase (2016) state that decisions tend to change over the time, therefore the urge to be agile is essential in a DMS. Agile in this context means easy to make changes in a relatively cheap way, which the author state, is necessary for organization to respond quickly and precisely. Integrating analytics into DMS allows organizations to make improved operational decisions, the authors argue that this due because of the fact that analysis on an organization's data may lead to new insights which influences the decisions. The last component of a DMS they present, includes that it should be adaptive. The authors state that organizations grow and learn over time and would therefore alter and test new things, DMS integrate such experimentation, in order for the organization to learn.

Taylor (2011) presents four principles as the key for DMS to bring business, IT and analytics together:

1. Begin with decisions in mind. There exists a shared challenge regarding decision making among Information Systems (IS). This challenge is two-folded and supposes that people using IS will make decision either automated or fixed. For the development of a DMS, it is required to start with thinking about the decisions.

2. Be transparent and agile. Nowadays, IS are obscure and difficult to modify. This results in slowly changing IS that require time and money consuming projects. Besides, when the code in is not clear, decisions cannot be checked or assessed whether they are correct. Agility is essential, because decision making within organization changes continuously. For this reason a DMS needs to be agile and transparent.
3. Be predictive, not reactive. Organizations tend to use their historical data as support for decision making. People use the historical data to predict what likely is to happen in the time to come. Using this approach for a DMS will not work, since a DMS does not include a human brain that anticipates on the historical data to foresee future trends. Therefore DMS must be provided with extrapolation, by e.g. (predictive) analytics, to be predictive, not reactive.
4. Test, learn and continually improve. The majority of IS have been developed in a way that one approach is used to take care of any decisions of the same kind. An IS will continue to behave as it is originally developed until the moment comes when code is changed to let the IS behave on a different way. The tremendous amount of data that is handled by IS might expose another best practice, however, the IS continues to behave as how it is programmed. A DMS requires another approach to be effective, it must have the ability to test and learn in order to improve itself.

As mentioned before, a DMS is a system that focuses on operational and repeatable decisions, these decisions are modelled in a way that they perform according to organizational preference. Decision making is increasingly more analytical as data driven organizations perform better on financial and operational aspects (Philips-Wren, Iyer, Kulkarni & Ariyachandra, 2015), which is why the performance of these systems are tracked and analyzed in order to improve the decision making process. A central role for improving the performance of a decision is the logic that is applied to the decision making, the logic defines how the decision should be made based in a situation and this is however - in contrary to the more traditional IS - not executed by code (Taylor, 2015).

2.2 Decision Automation

This chapter explains how manual decisions are to be modelled and automated. It outlines what Decision Automation (DA) is and the steps that are involved to encapsulate automated decisions into a decision service. The Decision Model Notation (DMN), a modelling standard, is presented and a commonly used technology to make the knowledge of the decision executable, Business Rules (BRs), is explained.

2.2.1 What is Decision Automation

The amount of data and knowledge, necessary to make a decision, expresses what is required to automate a decision (Fish, 2012). However, one of the main issues is to determine the extent of the overall decision automation (Cummings, 2006). Operational decisions are beneficial to automate, since operational decisions are characterized as decisions that require low amount of data and knowledge and this makes operational decisions more suitable to automate than strategic decisions (Fish, 2012). Automating decisions will contribute to the value of the Decision Management (DM) benefits and decision modelling helps to properly automate decisions by specifying those decisions (Taylor & Purchase, 2016). Decision Model and Notation (DMN) is a notation for modelling decisions that helps to bridge the gap between the specification of decisions and the automation of decisions (Object Management Group, 2016). A general introduction to DMN will follow in this section and an in-depth explanation of DMN is outlined in chapter 2.2.2.

A decision model can be created with the help of DMN, a decision model falls apart in two levels: the requirement level and the logic level (Object Management Group, 2016; Taylor & Purchase, 2016). Taylor and Purchase (2016) explain that the requirement level represents decisions that are decomposed in sub-decisions and are related to other artifacts, such as data input, knowledge or other decisions. They state that the requirement level is presented in a model, also known as a Decision Requirements Diagram (DRD) and shows explicitly what the dependencies of each decision are. The authors explain that in the logic level is determined what the output values are by specific input values. The logic that determines the output value may have one or more formats, for instance, BRs, decision table, analytical model or decision tree (Taylor & Purchase, 2016).

According to Fish (2012), the logic that is required to make a sub-decision, and eventually the whole decision, should be translated in a form that is executable and one that can be encapsulated into a service. He states that a frequently used technology, which is a form of knowledge that can be executed, are BRs. However, the author presents that for the creation, deployment and management of BRs a Business Rules Management System (BRMS) is required and the actual execution of the decision service occurs in the Business Rules Engine (BRE). The name may indicate that a BRMS and BRE are applicable for BRs only, however, this is not the case, because both software tools may also depict analytics and algorithms for performance improvements (Fish, 2012).

A part of DA is that decisions should be improved continuously; improving in the way not to only look where a decision can be improved but also determining processes that ensure improvement of the decisions over time (Taylor & Raden, 2007).

2.2.2 Decision Model Notation

The standardization report about DMN, presented by the Object Management Group (2016) state that the use of DMN may assist to bridge the gap between decision specification and decision automation. This section will go in-depth into DMN and according to the Object Management Group (2016), DMN has the purpose to present constructs that are used to model decisions. They present that it is introduced as a general notation that is comprehensible for all users in an organization and that DMN can be used in concert with the standard notation of business processes, Business Process Model Notation (BPMN). This means that the modelled decision can be related to specific business processes (Object Management Group, 2016).

Tasks, events and activities are designed in a business process in which the occurrence of decision making is compulsory and a DRD designs the decisions that occur in the business process, together with their connections and the specifications to bridge the gap with the decision logic (Object Management Group, 2016). The decision logic provides how an output of that decision is created. Figure 2.2-1 shows a reillustration of the context in which DMN is used (Object Management Group, 2016).

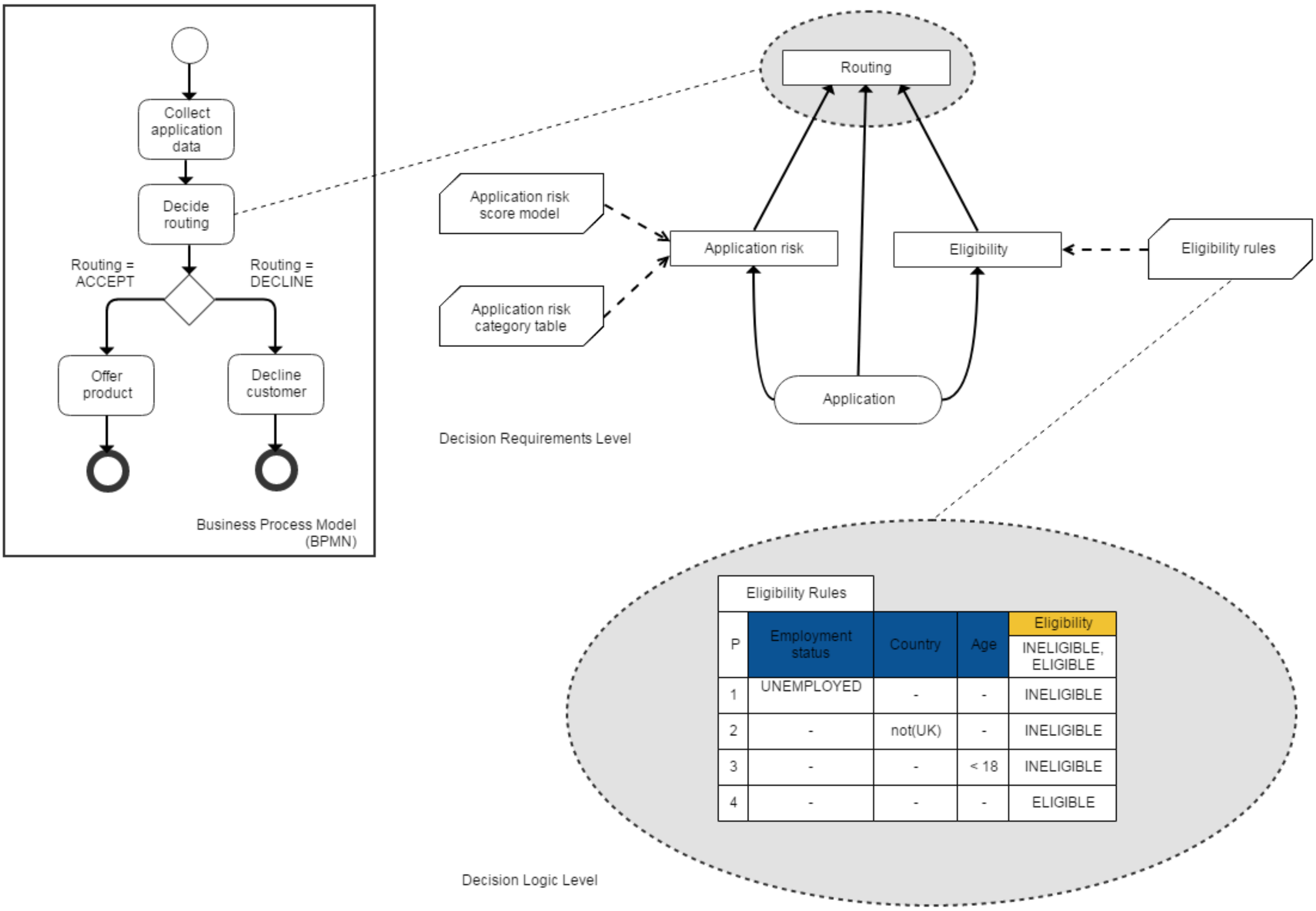

Figure 2.2-1: Modelling Aspects (Object Management Group, 2016, p.16)

The Object Management Group (2016) presents that the requirement level of DMN contains a Decision Requirement Graph (DRG), which presents the whole picture of how decisions are connected to each other and a Decision Requirement Diagram (DRD), which is a view on the DRG of a specific aspect. They state that modelling decisions in this way offers the possibility to scale down into sub-decisions, which is needed if automation of the decision is the purpose, because the outcome of a (sub-)decision can be clearly specified based on its input values.

The Decision Requirements Level of a decision model may consist of four elements, which are presented by the Object Management Group (2016): *a decision*, *business knowledge*, *input data* and *knowledge source*. The elements are shown in figure 2.2-2.

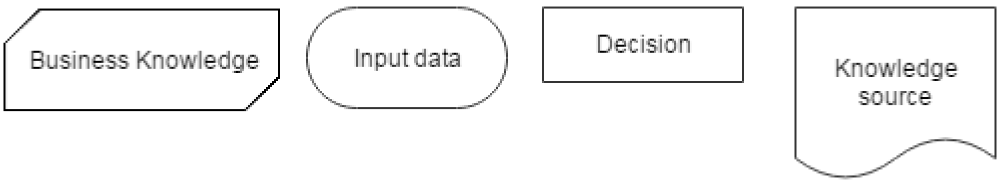

Figure 2.2-2: Elements of a Requirements Level (Object Management Group, 2016, p.30)

As the name of the DRD may suggest, in order to determine the outcome, a decision requires to have an input and the Object Management Group (2016) describes that the *input data* contains information that may be used by one or more *decisions* as input, which could be manually imported. The *decision* uses the *input data* to determine the outcome and then they state that the *decision* itself uses logic, decision logic that may require *business knowledge. Business knowledge* is explained as a model that contain knowledge of the business in formats like BRs, decisions tables or an analytics model and the fourth element is the *knowledge source*, which indicates the authority of each of the other elements. Figure 2.2-3 shows a simple DRD.

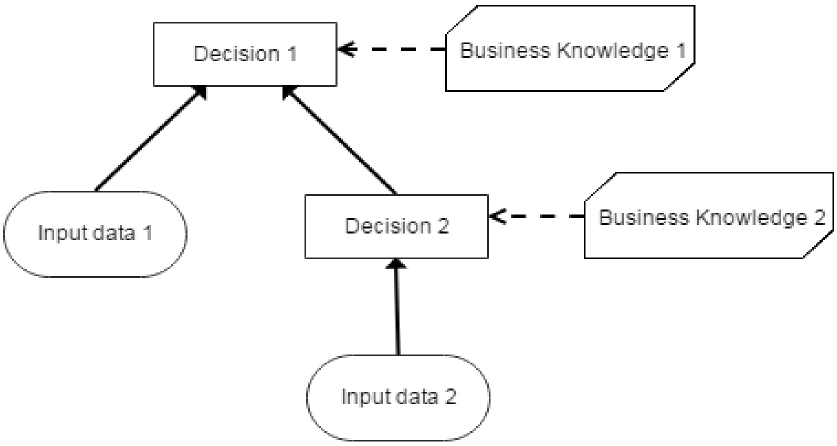

Figure 2.2-3 Example of DRD (Object Management Group, 2016, p.21)

The DRD as described in figure 2.2-3 is likely to be clear enough for business users to specify decisions, how decisions are related to each other, what the required business knowledge is and what the sources of the business knowledge are. Decision logic helps to achieve a level of further detail of these components and the overall purpose of the further specification of these components may results in automation of the decisions (Object Management Group, 2016).

Taylor and Purchase (2016) point out that the decision logic level is related to the requirement level, by defining the logic that is used to specify the outcome of a decision, based on its input. They present that the format in which this logic is presented can be influenced by many factors, for instance, the degree of expected changes, the level of complexity and the consistency of the knowledge that is required for the logic. Section 2.2.3 will introduce Business Rules (BRs) as a format for decision logic, because BRs are a modelling standard (Object Management Group, 2016) and are frequently used as decision logic (Taylor & Purchase, 2016).

According to the Object Management Group (2016), an organization most probably models decision logic with the purpose to automate it, which is done by using decision services. They state that decision services make one or several decisions available as a service that could be consumed and if a decision service is being called, it requires input and returns the output. The input consist data of all the encapsulated decisions in the decision service (Object Management Group, 2016). A possible difficulty arises when one or more decisions could serve as input for another decision, as for instance, can be seen in Figure 2.2-3. This may result in the question whether the definition of the input should be input data or decision (Taylor & Purchase, 2016). The solution is that the input also may consist of other decisions, so called input decisions, and the output of the decision service is the result of an assessment of one or more decisions, which is based on the input (Object Management Group, 2016).

The use of DMN as described above will result in a decision model. A decision model helps to understand the choices from a decision and therefore can be used to inform one about the extent to which a decision should be automated. Decision modelling can be used for both manual and automated decisions and according to Taylor and Purchase (2016), adapters of decision modelling may find benefits, which can work as motivators in five ways:

1. The use of decision modelling may help to lower time to market. Organizations can create a decision model to analyze, test and refine the decision logic, this means that difficulties with the specification of the decision logic can be solved so that the deployment can occur without the usual delay for debugging. Besides, the decision model supports the building of the infrastructure by determining the decision services.
2. The mentioned time savings above may result in lower development costs. In addition, other possible development costs may be saved when using decision modelling. When decision specifications are modelled, potentially flaws and inconsistencies can be detected and solved without executing the decision service. This may avoid expensive project of rework.

3. Another benefit of detailed decision modelling is more agility. Decision modelling makes it possible to conduct impact assessment in a very straightforward way. Decisions could be designed in a different way and then analyzed and assessed. The results in a faster implementation of changes as well as safer changes.
4. The use of Business Rules is often related to the IT department. The use of decision modelling, however, is not and therefore improves business engagement. Visualization with decision modelling shows the connection among important decisions, which enhances business analysts, in addition decision modelling can be used to simulate and champion test the decision while deployment is not necessary.
5. Greater scalability. The introduction of decision modelling ensures that decisions could be decomposed as sub-decisions. The DRD allows decisions to be modelled at a higher scale and working with this structure offers the possibility to let each part of a decision be handled by the most suitable specialist.

2.2.3 Business Rules

Organizations are challenged with BRs every day, although it might sound unimaginable, the use of BRs is inevitable these days (Nelson, Rariden & Sen, 2008). BRs define the logic on which decision outcomes are based (Taylor & Purchase, 2016). According to Meservy, Zhang, Lee & Dhaliwal (2012) a BRs can look like the following statement: *"If the customer is a preferred customer, discount the price of a product by 10 percent."* BRs are commonly notated beginning with an *if*-statement and concludes in a *then*-statement, depending on the input a specific output is given. BRs express the strategy of an organization and may be used to lead and manage the business, however, not all BRs should be automated (Von Halle & Goldberg, 2006). According to the Business Rule Group (2000), a BRs can be defined as follows:

> *"A statement that defines or constrains some aspect of the business which intends to assert business structure or to control or influence the behavior of the business."* (Business Rule Group, 2000, pp. 4-5)

BRs outline what a certain case has to be, or not, an executed rule therefore results in a constraint that is true or false which states that BRs determine the "what" rather than "how", in other words, the logic of a specific decision in a business model (Morgan, 2002; Graham, 2007). The paradigm of BRs originates from the areas of Artificial Intelligence (AI), traditional databases and Unified Modelling Language (UML) (Svensson & van Biert, 2014) and reflect on how the organization works as well as the intention of the organization would like to work (Morgan, 2002).

Morgan (2002) explains that rule statements as such are intended to be uncomplicated and tend to look unimpressive. A simple and obvious appearance of rule statements is a positive thing, since it means that the decision logic is understandable. Five characteristics are specified for business rule statements (Morgan, 2002):

1. Atomic: to make sure that a rule statement cannot be broken down further.
2. Unambiguous: to ensure a solely and obvious explanation.
3. Compact: to keep the statement short, preferably one sentence.
4. Consistent: to let all rule statements together be a logical and united description.
5. Compatible: to stick with identical terms within the whole business model.

BRs originate from the objective of an organization (Rosca, Greenspan & Wild, 2002), which assumes that BRs can be found within the organization. The discovery of BRs may become expensive if the organization is complex (Polpinij, Ghose & Dam, 2015). In his book Morgan (2002) argues that BRs are mainly found in documentation, tacit know-how, business records and other automation systems. However, there exists a distinction between three different BRs types and it is of interest for an organization to know the different types of BRs, because each type is to be found in different way. The types are:

1. Integrity constraints: these business rules are to be found in data of the IS.
2. Derivation rules: rules that may be retrieved from external information.
3. Operational rules: rules who explains the performance of an operation.

An easy and promising starting point is according to Morgan (2002) a static analysis, which is analysis of the available documentation helps to prevent the rediscovering of rules. He argues that these documents can be internal as well as external, internal documents belong exclusively to the eyes of an organization and are likely to be private and external documentation on the other hand, is more open to public.

Once rules are discovered, they will continuously be defined and refined, in order to ensure that BRs can be managed. Morgan (2002) presents requirements that are necessary for rule management, these are: (1) the modelling tool, (2) the rule definer, (3) a logic simulator and (4) a rule repository.

1. A modelling tool is used to model the logic of a decision based on a business model, which may be done by UML (Morgan, 2002) or DMN (Object Management Group, 2016). Subsequently, this logic may be deployed in a Business Rule Management System (BRMS).
2. A rule definer is a tool that supports a user in writing rules, it contains an environment in which templates with structures can be made and helps with referencing to the Business Object Model (BOM).
3. The logic simulator may be used to test different scenarios for a particular rule set. When an organization contains a lot of Business Rules, it becomes impossible to assess all of them manually. The logic simulator may use a simple spreadsheet with input data to expose unexpected flaws in the BRs.
4. A rule repository is used to store the BRs. The amount of Business Rules may grow rapidly in organizations, if automation grows. The rule repository will hold a role in the management and versioning of BRs, since it not only stores the definition, but the references between BRs and supporting details as well. (Morgan, 2002).

According to Stineman (2009), creating and maintaining of BRs can be done with the use of a BRMS, which allows an organization to define, refine, deploy and monitor decision logic. Figure 2.2-4 illustrates the different components of a BRMS. The use of a BRMS enables an organization to separate decision logic, executed in the Rule Engine, from an Operational Application, as illustrated in figure 2.2-4 (Stineman, 2009). A BRMS allows business users to manage BRs independently, in the Rule Development Environment, and to chain them in rulesets, in the Rule Repository. The three major components included in the BRMS are: a Rule Repository, a Rule Engine and the Rule Development Environment, tools that allow users to manage the decision logic (Stineman, 2009; Graham, 2007). An organization may benefit from using its data sources, right pane of figure 2.2-4, for analytical purposes because the results may cause an improvement in the automated decisions.

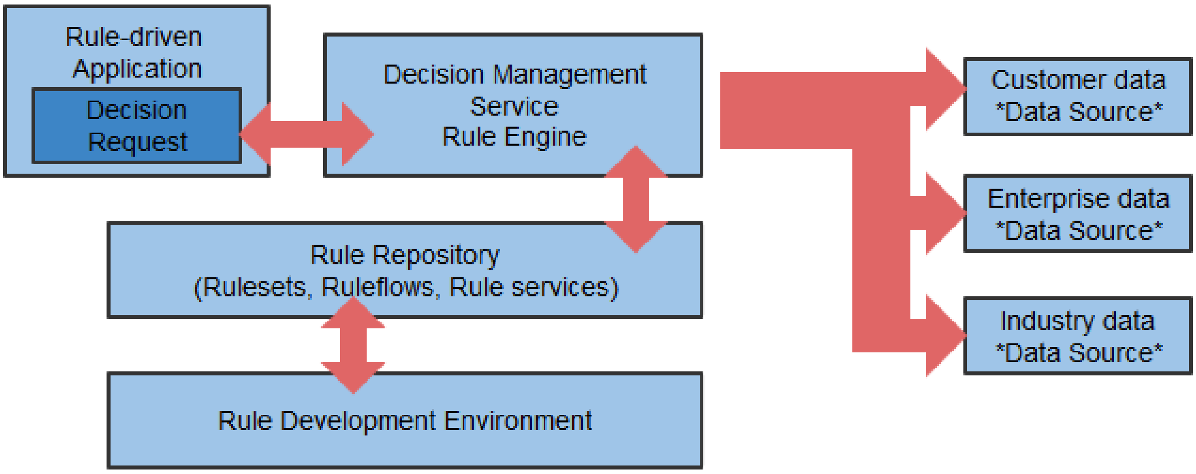

Figure 2.2-4: Components of a BRMS (Taylor, 2005, p.752)

2.3 Analytics

The previous chapter showed that DM can use analytics to design or maintain operational decision making. In this chapter the concept of analytics will be discussed as well as the various kind of analytics and how analytics is used in context.

2.3.1 Business Intelligence and Analytics

Business Intelligence (BI) and Business Analytics (BA) are terms that have been evolved strongly over the decades (Chen, Chiang & Storey, 2012). Whereas the concept of BI originated from early 1990s and focused on data collection, extraction and descriptive analysis technologies, later, in the 2000s a new concept emerged called Business Analytics which served as the analytical component of BI (Chen et al., 2012). For the sake of clarity we will use the term analytics as the definition of both BI and BA, as other authors and scholars used a definition to use these concepts interchangeably before us (e.g. Chen et al., 2012; Someh, Wixom, Davern & Shanks, 2017).

Organizations continue to see the importance of gathering extensive and high qualitative data, nowadays data is even considered as a primary business asset (Abbasi, Sarker & Chiang, 2016). Integrating and managing data are crucial in facilitating business processes as well as decision making (Abbasi et al., 2016). Data-driven organizations perform better on operational and financial aspects than non-data driven organizations (Philips-Wren, Iyer, Kulkarni & Ariyachandra, 2015). The concept of transforming data into something that helps decision makers make decisions for the organization is explained in the information value chain (Abbasi, et al., 2016). Pearlson and Saunders (2004) state that the chain is a cyclical set of objects that transform data into information and knowledge through analysis. They define data as a set of objective facts or observations, which has no intrinsic meaning on itself. The data is organized, analyzed and transformed into information and according to the authors, information with the most value is considered knowledge. The knowledge can help support decision makers in making decisions, which ultimately results in actions (see figure 2.3-1).

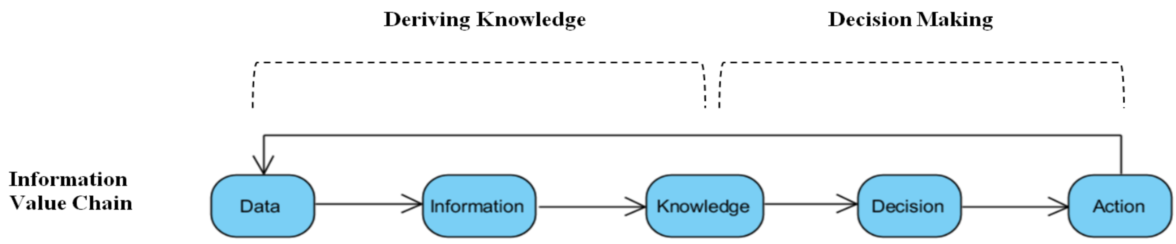

Figure 2.3-1: The Traditional Information Value Chain (Abbasi et al., 2016, p.4)

Analytics can be considered as a collection of decision support technologies for organizations to combine data gathering, storage and knowledge management with analytical tools that present information to enable effective decision making and management support to make better and faster decisions (Negash, 2004; Chaudhuri, Dayal & Narasayya, 2011; Işık, Jones & Sidorova, 2013).

Analytical technologies are among top priorities within the majority of successful organizations. Organizations have leveraged such technologies to increase its service and overall efficiency e.g. customer support, financial claim analysis, fraud detection and user profiling (Işık, et al. 2013; Chaudhuri et al. 2011). Işık et al. (2013) argues that analytics help organizations understand what is happening and what is likely to happen in the future. They explain that the primary purpose of analytics is to aid organizations in making decisions and when used correctly, the success of analytics may translate in benefits such as: reducing costs, improve efficiency and improve profitability.

Analytics and decision support system research have a strong and valid place in the rapidly changing IS research industry over the last thirty years and will continue to do so in the future

(Hosack, Hall, Paradice, & Courtney, 2012). As analytics traditionally were viewed as tools to support decision making on a strategic level, they are now being utilized for a broader range of capabilities and business activities including the operational and tactical level (Elbashir, Collier & Davern, 2007). Elbashir et al. (2007) argue that the new developments make it possible for managers to make better and faster decisions due to the access to more information. Analytics has evolved and is nowadays able to analyze data from unstructured and complex contents, dealing with an increase in data volume and is able to structure it from a variety of different sources (Chen et al., 2012). Analytics also provide insights to what has changed as well as how organizations should react to it, grasping new business opportunities (Russom, 2011).

2.3.2 Kinds of Analytics

Recent developments within analytics allowed organizations to track what customers are saying about a service, how satisfied they are and if a customer is likely to come back to use the service again (Mathew, 2012). The use of analytics allow organizations not just to know what customers want, but also what price customers are willing to pay, what factors make them buy more from your organization and predict how many products a customer will buy in a lifetime (Davenport, 2006). According to Taylor and Raden (2007), analytics can be used to outperform or outthink competitors. Organizations that pursue strategies based on analytics are likely to have an advantage in this global competing world as they increase the value by deriving information from their processes (Davenport, 2006).

Analytics can be divided and seen from three different perspectives, descriptive analysis (what has happened), prescriptive analysis (what should we do) and predictive analysis (what will happen). Evans and Lindner (2012) explain the different kind of analytics as follows:

- *Descriptive analytics.* Descriptive analytics is about showing and summarizing historical data into meaningful visualizations. The analytics can show how much has been sold in a specific region, which product has been sold the most and which business unit has the highest productivity.
- *Prescriptive analytics.* Prescriptive analytics can identify what the best course of action is. Based on various scenarios it can maximize or minimize a certain objective e.g. an advertising strategy or investment strategy that can minimize risk.
- *Predictive analytics.* Predictive analytics are used to analyze historical data and past performance to look forward and try to predict the future. These kind of analytics try to detect patterns within the data and find relationships between entities to better understand customer behavior or to optimize existing processes. Examples of predictive analytics could be identifying potential stolen credit cards based on an anomaly in the charges, a shift in the most profitable customer segment or prediction of the amount of sales based on a specific pricing of a product.

Since making correct business decisions can only be done if the decision is based on large volumes of external and internal data, analytics are therefore an increasingly value research area (Trkman, McCormack, De Oliveira & Ladeira, 2010). The literature states that especially predictive analytics are an interesting and upcoming tool for organizations to invest in, as it can uncover hidden patterns to anticipate the future (Eckerson, 2007). These organizations should first master basic reporting (e.g. descriptive analytics) in order to excel and invest in predictive analytics (Eckerson, 2007).

2.3.3 Analytics in Context

Even though analytics have matured over time and will continue to do so in the future, the key concept of supporting in decision making has not been changed. Analytics facilitate in better decision making in complex structured and unstructured decisions (Hosack et al., 2012). It helps in understanding and handling large numbers of data, addition to that, it helps organization see fluctuations within the data to see opportunities and threats.

As mentioned before, analytics follow the same principles as stated in the information value chain; transforming data into knowledge which helps decision makers take decisions and ultimately result in taking actions. The idea of analytics providing systems is that they can provide information at the right time, increasing the quality and efficiency of aid to the decision process to support decision makers (Negash, 2004). The data obtained often comes from various data sources and is usually stored in multiple databases across different departments within an organization and gathered data from all these different data sources is difficult to process as it differs in quality, formats or inconsistent representations (Chaudhuri et al., 2011). Therefore, it must be extracted, transformed and loaded in a way that it is prepared for further processing. Preparing such data is generally referred to as ETL (Extract, Transform and Load) and is done by database administrators, ETL developers or database managers.

Once the data is prepared, the data is stored in data warehouses. The data warehouses are managed by data warehouse servers and are complemented by specialized servers that provide extra functionalities for different kind of scenarios (Chaudhuri et al., 2011). The data stored in the database is then analyzed by data analysts that use Structured Query Language (SQL) to get a specific value from the data that can be used for decision making (Abbasi et al., 2016). With Online Analytical Processing Tools (OLAP) and other reporting tools, organizations are able to explore to get a broad spectrum view of the data and enables the illustration of data in the form of spreadsheets, Key Performance Indicators (KPI) and other visual dashboards (Chaudhuri et al., 2011). With the visualizations of the data, the organization can keep track of how the organization is performing. Adding to these business reporting possibilities, with the use of statistical analysis and data mining techniques it is possible for organizations to depict different kind of analysis to get deeper knowledge of their business e.g. regression analysis, anomaly detection, data clustering and predictive modelling (Chen et al., 2012).

By converting data into information and ultimately knowledge, an organization knows how it is performing and how it can be improved on a strategic level and is able to make timeliness efficient decisions on an operational level (Abbasi et al., 2016). Analytics help organizations understand their own position, in regards to competitors and customers. Some of the tasks performed by analytics, as stated by Negash (2004), are; strategic insights, impact analysis based on different scenarios and creating forecasts based on historical data. In order to succeed in these tasks certain factors needs to be met. These factors include support from senior management that drive the use of analytics, proper alignment between analytical strategy and business strategy, effective governance, users need the right training to use such tools and the use of analytics should be part of the corporate culture (Watson & Wixom, 2007).

2.4 Outline of Concepts

The need for organizations to have consistent and precise decision making plays an ever more important role (Nelson et al., 2008). The growing amount of IS and its complexity within organizations result in the challenge to keep consistency among IS (Nelson et al., 2008). Theory states that DM can play an important role in increasing such performance as it centers on automating day-to-day operations (Taylor & Raden, 2007). DM offers effective decision making, contributing to an increase of accuracy, consistency, agility of the decision making and reducing the time and costs to make such a decision (Fish, 2012; Taylor & Purchase, 2016).

The business model of an organization contains process logic and decision logic, which are related to each other. Process logic corresponds with the Business Process (BP) of an organization, which is concerned to convert input to output. Decision logic, which may corresponds with BR, is needed by process logic in order to run through a flow of activities and events. The decision logic produces true or false values and also numerical values (Holmberg & Steen, 2011). The values of decision management is optimal only when the knowledge for decision making, e.g. BRs, is captured in a system that automates decisions, a Decision Management System (Fish, 2012). This can be done with a BRMS, containing a rule repository in which Business Rules are stored, a Rule Engine, that executes rule services and tools in which rules can be refined, the Rule Development Environment (Stineman, 2009; Graham, 2007).

Analytics provide insights from data to support decision making, by evaluating past performance and predict future trends (Someh & Shanks, 2015). Analytics can show an organization what has changed and how organizations should react to these changes, grasping new business opportunities (Russom, 2011). By analyzing data and converting it into information and knowledge, decision makers can make better decisions (Abbasi et al., 2016). Better decision making may results in improved overall efficiency, reducing costs and improve profitability (Işık et al., 2013). As theory showed (Taylor & Raden, 2007), DM, specifically decision modelling, is supporting the use of analytics in DA. When an organization has automated decisions, it is likely that an organization would like to embed the analytical results into the DA, the use of decision modelling supports in orchestrating how decisions with an analytical model are implemented. (Taylor & Purchase, 2016).

The use of analytics in the context of DA, and specifically BRs, is two folded. Analytics can be used as a technique to acquire rules from (historical) data. Also, analytics can be used to create a model that predicts and enlarges the information that is used to make rules. The second case can be seen as an explanation of predictive analytics (Taylor, 2009). Analytics can be of high value when integrated in automated decision making, but when integrated wrongly, it can have severe consequences on business as poor decisions lead to poor results (Davenport, 2009). By this line of reasoning identification of the influences of analytics in automated decision making can help extent both Decision Support as well as Decision Automation research.

3 Research Methodology

The research in this thesis is aimed to expose the values that analytics have for a decision service. By doing so, data is collected in different ways and subsequently analyzed. The research is also set out to broaden the scientific evidence on this topic, which is a contribution to the body of knowledge as it improves the collections of scientific evidence (Recker, 2013). This chapter explains how data is collected and what analytical methods are applied, starting with the context in which the research has been conducted.

3.1 Context Selection

The domain we ended up targeting for the research was consultancy companies with an expertise in implementing Decision Management (DM) or Decision Automation (DA) solutions, and companies that utilize such solutions to perform their daily operations. The original plan was to target companies in the financial industry (e.g. banks, insurance companies) as they work a lot with repetitive, automated decision making. However, these companies were not keen on participating in interviews as they often thought information about these subjects are too sensitive and due to other compliance reasons. Consultancy companies are more likely to talk about what they do because it is part of their job prescription to talk about these subjects in order to sell their expertise. To add on that, consultancy companies have tons of experience and knowledge within the DM and automation field and can provide a broader view on the subject with specific examples.

3.2 Research Strategy

Today's rapidly changing world demands organizations to automate their process to increase its overall business value (Wixom, Yen & Relich, 2013). The vision of the research is that a growing number of organizations is making use of their data as well as automate internal decisions. The purpose for many organizations is to reduce cost and make processes run either more effectively, efficiently or both. The vision of the researchers in relation to the context of the research can be explained as follows: as the environment in which organizations operate is changing, it is likely that the automated decisions are changed likewise. The research tries to expose what influences the use of organizational data, specifically analytics, may have on automated decision services.

Randolph (2009) points out that the key in writing and achieving compelling research is to understand the literature in the field. Before conducting the research, essential literature on the topics of Decision Management, Decision Automation and Analytics have been read and analyzed to produce valuable research. Valuable research, in the eyes of the researchers, includes asking the relevant and right questions that would add value to current knowledge. The main research method is a qualitative approach. Qualitative study has the best fit for the research with its purpose to understand a phenomenon in a specific context and argues for a focus on textual data (Recker, 2013). The qualitative strategy can be related to the explorative character of the study that focuses on the discovery of formerly unknown findings. The research is rather exploratory and focuses on a phenomenon within a real-life context as it essential to get the reason why the different concepts are used. Gummesson (2003) argues that all research is interpretive, and therefore the research that will be conducted to answer the research question is interpretive. As stated by Orlikowski and Baroudi (1991), people tend to create their own subjective and intersubjective meanings as they interact with the surrounding around them. However, because the research is set out to explore and to discover how experts in the field of DM and DA utilize analytics for value towards a decision service, these people’s views are better expressed in words than in numbers. A qualitative research approach could provide better results of this limited discovered research field as e.g. a quantitative research approach, where specific measurements are being done which offer less opportunities for explorative research (Recker, 2013). Qualitative methods used to obtain the data will consists of interviews, which is a common tool for such a research method (Recker, 2013).

The literature provided insights and compelling topics to conduct research in. Based on the literature, three themes were proposed which are used as a guiding red line throughout the research. The three themes, as mentioned in the first part of the research, are Decision Management, Decision Automation and Analytics. A final thought for conducting the research and the research strategy is that the researchers also have the obligation to be passionate explorers trying to uncover new information, rather than using fixed research rituals (Gummesson, 2003).

3.3 Literature collection

In order to perform significant research, one must first understand the literature in the research field (Randolph, 2009). Academic literature and theories are the core at any research process as it provides the researcher guidance where to focus the attention within the field (Recker, 2013). By studying previous literature and research, the researchers got an extensive and broader understanding of DM and the topics within this field to investigate further on. This section presents how the theoretical data is collected.

Based on a pre-study, three themes were chosen that could provide insights for answering our research question. The three themes emerged were, Decision Management, Decision Automation and Analytics (see chapter 2). The majority of the literature has been collected via Google Scholar and the online university library, LUBsearch. The three themes provided the basis for the online searches. Appendix 2 provides a compilation of the literature used per theme. The main theoretical data for each theme is collected based on the following search terms:

- Decision Management: “Decision Management”, “Decision Management Analytics”, “Decision Management Business Rules”, “Enterprise Decision Management”, “Business Decision Management” and “Decision Management Systems”
- Decision Automation: “Decision Automation”, “Decision Automation Techniques”, “Decision Automation and Decision Management”, “Decision Model Notation”, “Decision Services”, “EDM Business Rules”, “Improving Business Rules” and “Quality Business Rules”
- Analytics: “Analytics”, “Business Intelligence”, “Big Data”, “Business Analytics”, Business Process Execution”, “Trends Analytics”, “Trends Business Intelligence”, “Business Intelligence capabilities”, “Big Data Trends”, “Analytics Research in IS” and “Kind of Analytics”

The search terms resulted in valuable literature for each theme individually, however very limited literature has been found in relation to the values and effects of analytics in automated decisions services or how these combined concepts are applied in practice. This confirmed the fact that further research in this area is needed because it can assist in connecting theory to practice and potentially discover new insights.

In addition, already known literature from the courses of Business Intelligence (INFN45), Business Decision Management (INFN50) and Research Methods (INFN01) has been used. Besides the course literature and the results of Scholar and LUBsearch, several papers from James Taylor, a guru in the field of Decision Management, were used and retrieved from Google searches.

3.4 Informant Selection

The first criteria on which the informants for the research has been chosen was based on the knowledge and experience within the field of DM and DA. Informants should either have a background in working with these concepts on a daily basis or are experts in this area of expertise and help organization with applying these concepts.

However, finding participants for the research was a long lasting and difficult process. As mentioned before in the context selection, organizations in the financial industry were the first to be contacted. Financial organizations are information sensitive and from own experience the researchers know that they are likely to have a large amount of operational decisions. A number of financial organizations are also *capital partners* of Lund University. Five capital partners were therefore approached by email with a response of two and an actual number of zero participants. It was difficult to get participants, due to the fact that the researchers did not know beforehand whether a person had knowledge or experience with DA or DM. To counter this, employees from financial organizations in Sweden were also contacted via LinkedIn, which ensured certainty about the experience and knowledge of a person.

The financial organizations that were approached were Hansdelsbanken, SEB, Nordea, Swedbank, Spårbanken and Danske Bank. A total number of 24 persons were approached through email and LinkedIn, which resulted in zero positive responses for willing to participate in the research.

In order to increase the chance of finding participants, the search was extended and reached out to participants in The Netherlands. Both of the researchers are from the Netherlands, which was beneficial in online searching for Dutch participants. The following organizations were approached: a tax agency, an immigration service, multiple insurance companies and a consultancy firm. From the fourteen persons contacted, only the consultancy firm replied and was willing to participate in an interview. As a last resort, the researchers placed a message on the forum website Reddit. The website consists of many pages where experts and non-experts can discuss different topics. The message was placed and asked for participants in the field of DM and decision automation for conducting in a short interview. A total of zero potential participants responded.

An alumni student who has been working in the field of DA was contacted as well and was willing to participate in an interview. It turned out to be a great help for this research, as he provided a list of potential participants that would be interested for our research and who he worked for in the last couple of years.

An overview of the participants that were willing to participate in an interview can be found in table 3.4-1. The participants are anonymous and are given a code instead. The position and organization may present the kind of persons that has been interviewed. The far right column presents the date of the interview.

Code	Organization	Interview type	Date
P1	RuleManagement Group	Skype	April 28th, 2017
P2	SuperGraph	Skype	May 5th, 2017
P3	Decision Management Solution	Email	April 28th, 2017
P4	Goldman Sachs	Skype	May 9th, 2017

Table 3.4-1: Overview of interview participants

3.5 Empirical Data Collection

The main method for collecting empirical data for this research was by conducting interviews. The interviews had a semi-structured approach, where several fixed questions were proposed but also additional questions were asked during the interview itself. An interview guide (see section 3.5) was used that state the fixed questions. The non-fixed questions were mainly focused to clarify an answer or to perceive potential future developments. In order to assure the quality of the data collection obtained by the interviews, seven guidelines of Myers and Newman (2007) were followed. Myers and Newman (2007) present seven guidelines with the purpose to achieve excellent performance when conducting an interview. An overview of the content of the guidelines is presented:

1. *Situating the researcher as an actor.* This implies that the distinction of the roles, especially from the interviewer, are clarified. This study intended to do so by sending an interview guide with instructions and expectations on beforehand.
2. *Minimize social dissonance*. An uncomfortable environment during an interview may cause twisted answers. Therefore, minimizing the change of an uncomfortable feeling of an interviewee is important, here we pronounced our preference of an interview by Skype, which offer the possibility for the interviewee to choose a comfortable environment to speak.
3. *Represent various voices*. Meaning interviewing various people within an organization. Different people have different perspectives and opinions. In this study, it was difficult to get participants who were willing to participate. However, several persons with the same position in their organization were able to participate.
4. *Everyone is an interpreter.* This means that subjects and the context may be interpreted differently, between the interviewers and the interviewee. Interpreters can cause that subjects are viewed differently based on their view.
5. *Use mirroring in questions and answers.* This is used during the interview. It entails that questions and answers regarding the interviewee are formulated with the same words that the interviewee uses. Examples are shown in appendix 3 until 6**.**
6. *Flexibility.* Flexibility is often used at semi-structured and unstructured interviews. This study contains semi-structured interviews and that requires flexibility of the interviewer to explore interesting research lines as well as to keep the interview in line. This resulted in situation where questions has been asked in order to get more in-depth of a topic.
7. *Confidentiality of disclosures.* This has to do with how the records and transcripts of the interviews are being handled. Firstly, the interviewers were willing to sign an agreement for disclosure, if necessary. After interviews were conducted, the transcription was sent back to the interviewee for a check. When the interviewee accepted the transcription it was used for the analysis.

Keeping the guidelines in mind, the data collection for the interviews followed a method similar to conducting *Appreciative Interviews*. As described by Schultze and Avital (2011), appreciative interviews searches for the best in people and the relevant world around them. Alternating between retrospective and prospective reflection and they describe that appreciative interviews are designed to reveal “what is” and expanding it to a potential futuristic sight, “what might be” (see figure 3.5-1). The method is set out to facilitate in insightful discoveries and learn about the interviewee’s experiences, which fits therefore perfectly for the research. By doing so, the researchers hoped to collect rich data about the interviewees lived experiences and their view and meanings on the subject (Schultze & Avital, 2011).

Interview Phase	Retrospective	Prospective
Guiding question	What is	What might be
Elicitation mode	Concrete Experiences	Abstract conceptualization

Figure 3.5-1: Example process of an Appreciative Interview (Schultze & Avital, 2011, p.7)

Interviewees have the possibility to share their stories freely and openly, that set out to share a reflection of own experiences first and build up to potential future scenarios. The questions formulated for the interview were based on these concepts and followed a process similar to this. Conducting the interview through a positive lens, only interrupting to clarify something and let the interviewee talk as openly as possible.

There is one anomaly when it comes to collecting the empirical data through interviews, one interview is conducted through email. The schedule of the participant was too packed to conduct a Skype interview and therefore requested to send the questions by email.

3.6 Interview Guide

An interview guide (see appendix 1) has been developed in order to prepare the participants for the research objective and describe a general introduction on the topic. The interview guide was sent in advance (approximately one week before the interview) to the participant to get a feeling of what the research is set to find out and the line of questioning the participant should expect. By sending an interview guide in advance, the researchers hoped to get a more extended answer than when a participant would hear the question the first time during the interview, as the research has an exploratory emphasis. Also, one interviewee was able to inform us on beforehand that certain questions were not applicable for him to answer. This made it possible to focus more on the other questions.

The interview guide is divided into three sections. Firstly an introductory question is proposed to get familiar with the background of the interviewee and the company where he or she is working for. The second section consists of the main part, where specific questions regarding the three themes were asked. The last section contains the closing part where the end comments of the interviewee regarding the topics are requested. Before starting each interview, the interviewee got notified on several formalities such as anonymity, confidentiality, voluntary participation, and disclosure which are presented in section 3.5.

3.7 Analytical Method

The data in this research is collected via two ways, the study of literature plus textual data and conducting interviews. In addition to reviewing and analyzing academic literature, which is crucial in doing any kind of academic research (Webster & Watson, 2002), reports from practical perspective and manifesto's were scrutinized as well. However, the core for conducting this qualitative research lies with the data obtained from the interviews. In this section is explained what methods for analyzing of the interviews is used. Starting off with how the data is transcribed and continuing how the data is coded and used for the empirical results.

3.7.1 Transcribing

The intention was to conduct all the interviews in English, however, since the researchers and three participants are Dutch, some of the interviews were conducted in Dutch. The reason for this is that the interviewees would not be restricted to their English spoken skills and therefore could provide more detailed and in-depth answers on the interview questions. All the interviews have been recorded with the exception of the emailed interview. By recording the interviews, the interviewers could focus on the actual interview itself and the answers the interviewee gave without having to remember what has been said (Kvale & Brinkmann, 2015). The interviews conducted in Dutch were translated and transcribed in English before being further analyzed. The first transcription and translation of the interviews has been divided equally over the authors. In order to enhance the quality of the transcripts, the transcripts received a final check-up by the interviewee to confirm the content of the transcripts are correctly stated. During the writing of the transcription, words such as *"ah", "uhm", "er"* and "*hmm" were* omitted. An overview of all transcriptions can be found in appendix 3 until appendix 6.

3.7.2 Coding

To ensure efficient analysis of the transcripts, the authors applied codes, which resulted in a total of 39 pages of transcripts, containing 69 sections of codes to transcripts for each specific context that is relevant for the research. Kvale and Brinkmann (2015) argue that coding is generally referred to as applying keywords to pieces of text, the most important findings of the interview are marked with coding. The analysis contained two approaches for coding, selective and open coding. Selective coding means that one or more codes are defined, which represent the core the whole interview (Recker, 2013). The code themes are equal to the themes of the literature review. Each code represents a different objective as showcased in table 3.7-1.

Theme	Literature	Objective	Code
Decision Management	Chapter 2.1	Showcasing the importance of DM and the ability to explain the value of Decision Management	DMT
Decision Automation	Chapter 2.2	Explaining the role of Decision Automation, techniques to automate decision and responsibility for maintaining the automated decisions	DAN
Analytics	Chapter 2.3	Showcasing how analytics adds value to automated decision making and how analytics are used for designing and maintaining automated decision making	ANS

Table 3.7-1: Selective coding overview

In addition, open coding is applied. Open coding is used to expose relevant concepts in the transcripts (Recker, 2013) and is shown in table 3.7-2. The open codes that are found have been given a description and a parent code in order to group the open codes on a higher level. The parent code relates to of three themes.

Open code	Description	Parent code
DMV	Decision Management Values	DMT
REL:DMDA	Relation between DM and DA	DMT / DAN
RDY	Rule Discovery	DAN
AUT	Automation Techniques for the Decision Logic	DAN
MAI	Maintenance/optimization of the automated decisions	DMT / DAN / ANS
REL:DMAN	Relation between DM and Analytics	DMT / ANS
MOD	Modelling techniques for decisions	DAN
REL:DAAN	Relation between DA and Analytics	DAN / ANS

Table 3.7-2: Open coding overview

Coding ensures to get the key points out the transcript and to reduce the less meaningful data (Recker, 2013). To achieve a better quality of the coding, the coding has been done by both authors separately. This implies that the same transcript is coded two different times. The two separate coding were then compared and discussed to ultimately result in a final coding transcript of the interviews, which can be found in appendix 3 until 6. By having two perspectives in identifying relevant coding in the interview, the total of the research validity and reliability increased (Recker, 2013).

3.8 Research Quality

In order to achieve and obtain high quality research, reliability and validity factors are considered when conducting the research. In this section these factors will be further explained, as well as the ethical principles that has been followed during the interviews. The ethical principles intent to make the interviewee feel comfortable with providing empirical data for the research.

3.8.1 Reliability

Reliability extends to variables that are consistent to what it was intended to measure (Recker, 2013). Meaning if the same constructs are measured multiple times, the same results will persist (Bhattacherjee, 2012). This research ensure such reliability by measuring the same construct (coding the interview transcripts) by two observers (Bhattacherjee, 2012). This allows for two different based views on the obtained data and enhances the total of the reliability of the research (Recker, 2013).

3.8.2 Validity

Conclusions may only be valid if the data obtained is accurate (Recker, 2013). In order to increase the validity for this research, the transcripts of all conducted interviews are verified with the participant of the interview. This ensures that the data obtained from the interview is indeed correct and accurate. It is always possible that during the interview incorrect information is given, but with this verification the possibility of incorrect data is limited as the participant has the opportunity to correct the incorrect data.

Another aspect to enhance validity for the research is to make sure that the data collected is valid for what the research is set to find out (Recker, 2013). Therefore the fixed questions from the interview guide are there to provide a general line to ensure the data collected points towards answering the research question.

3.8.3 Ethics

Ethical responsibility is of importance and Bhattacherjee (2012) mentions four principles of ethical behavior. These principles are followed during the study and presented in the interview guide. The core of each principle is mentioned below:

- Voluntary participation and harmlessness, which means that the interviewees were familiar with the fact that their input for the study is voluntary and that they had the freedom to stop with participating at any time without consequences.
- Anonymity and confidentiality, this principle states that all participant were protected in the study. Which means that other readers or researcher will not be able to identify the participants of the study as well as that an individual's identity will not be revealed in the report.
- Disclosure means that participant received information of the study on beforehand, in the form of an interview guide. This is to provide the participant with a basic understanding of the study and to help them deciding whether they wish to participate in the study.
- Analysis and reporting. The data collected from interviews was intended to be used for analysis and to draw a discussion.

Interviewees were notified at the start of each interview on these ethical guidelines to assure that the objective of the study is clear and the interviewee voluntary wants to collaborate with the research.

3.9 Reporting

The main findings of the research will be reported in the form of quotes obtained from the interview transcripts. The empirical results chapter of this research contains the most valuable and interesting results, which are highlighted by direct quoting from the interview transcripts. The research is exploratory and is set out to compare different experiences from the participants in order to perceive a better understanding of the value of analytics for a decision service. Quoting is an appropriate method to compare these different views and experiences and puts them into context.

4 Empirical Results

In this chapter we will showcase the obtained empirical results as followed by the research methodology from chapter 3. This chapter will present and describe the results in a thorough way by using direct quotation from the interview transcripts. This chapter is divided into two parts. The first part gives an overview of the interviewed organizations. The second part describes the analysis of the empirical results from the conducted interviews.

4.1 Organizations

The results for the research are based upon the interviews conducted with several individuals working with Decision Management (DM) and Decision Automation (DA). The individuals working for various organizations provided the research with insights of how they operate their business as well as how they look at the different relevant concepts in regards to the research. A brief description of each of the organizations that participated in the research will be given in this section.

4.1.1 RuleManagement Group

RuleManagement Group (RMG) was founded in 2005 to establish new innovations on the subject of rule management in the field of management and control for laws and regulations. (RuleManagement Group, 2017). According to their website, RMG is a leading company in organizing and advising regulatory control and the services they provide include analyzing and modelling knowledge to develop processes for decision making and organize these processes in a way that it can be properly maintained and controlled. The website states that the company developed a method to derive rules from laws and regulations and transform it into executable services. The clientele of RMG include many governmental as well as insurance organizations (RuleManagement Group, 2017).

4.1.2 Goldman Sachs

Goldman Sachs was founded in 1896 and is an internationally operating investment bank. Goldman Sachs is specialized in providing financial services to governments and multinationals, the company also advises businesses on raising capital or manage risks, manage assets for institutions and invest capital in order to grow (Goldman Sachs, 2017). The company utilizes Decision Management solutions for many of its operational decisions and projects.

4.1.3 Decision Management Solutions

Decision Management Solutions was founded in 2008 to help organizations make data-driven decisions by applying Business Rules (BRs), analytics and other similar technologies (Decision Management Solutions, 2017). As explained on their website, Decision Management Solutions are experts in the field of decision modelling and Decision Management for banking, insurance, retail and manufacturing. Besides that, the website explains that the company helps organizations with business architecture, process automation, analytics requirements and rules analysis when applying data-driven decision making and such decision making delivers significant benefits as it improves operational and overall business performance.

4.1.4 SuperGraph

SuperGraph was founded in 2014 and puts predictive analytics at the core of its business to reduce uncertainties and help organizations make more informed decisions and by doing so, delivering business benefits with each decision (SuperGraph, 2017). According to their website, the organization tries to uncover valuable insights out of the organization’s data and derive meaningful information from it. The company SuperGraph tries to improve decision making by allowing organizations to learn from past experiences and use these experiences in future decision making (SuperGraph, 2017).

4.2 Analysis of Results

In this section of the research the empirical results of the collected data will be showcased. The transcripts of the entire interviews can be found in appendices 3-6. The transcripts have been coded as states by the guidelines in chapter 3.6, and will follow the three main themes as structure: Decision Management, Decision Automation and Analytics. The results refer to the transcripts in the appendix as e.g. (2:12), citing transcript participant 2 and line number 12.

4.2.1 Decision Management

The interview was made to discuss the broader areas of the research before narrowing down on the specific topic of the research question. The first set of questions aimed at the perspective of the participant on DM and how they would describe it.

Generally, the view on DM is seen as an approach that an organization can use to create, maintain, execute and optimize decisions. One participant argues that the use of DM has the objective to make better decision. This is not explicitly stated by the other participants, but they argue that DM involves an analytical component for the optimization of decisions:

"The whole of analyzing and making explicit, describe, maintain and control but especially organization of a process for decision making within an organization." (1:6).

Also, one of the participants states that the use of DM can be seen as a capability to realize changes in the organizational behavior:

"I would describe decision management as a business capability that is mainly responsible for delivering change by developing "executable" decision artefacts that subsequently provide transparency, traceability for business making. […]." (4:2).

The types of decisions that are likely to be automated are operational decisions. That operational decisions are the specific type of automatable decisions is supported by each participant. Strategical and tactical decisions need different kind of information and are therefore more difficult to automate:

"Absolutely, without a doubt. It is often focused on operational decisions." (1:18).

The purpose of DM is to improve the decision making process for operational decisions, which involves the execution of automated decisions. It is argued by all participants that the DM should have the purpose to automate decisions. However, one participant argues that a DM without automated decisions would be limited:

"[…] Because you remain with the same resources, the same context, you are not sort of thinking outside the box, thinking about how could we completely, from holistic view re-design or re-engineer these processes. It is the same with decision management in that sense, if you not automate it […]." (4:23).

After being asked about the general view of DM, the interviewers continued by asking what the value of DM for an organization is in their opinion. The values of DM, as presented in the theoretical data, form a minor similarity with the values of the collected data from the interviews. The only values that is being achieved according to theory and practice are agility, accuracy and consistency. The latter value is especially realized when DA complements the DM.

"Well, the thing you are looking for as an organization is to find a way in which decision are made in the most consistent way. A large part of this will be realized by automating decisions." (2:50).

"The value is quite diverse [...]. Agility is an aspect of your architecture, in other words as an organization you should think where agility is important. Agility is important part in regards to flexibility towards the business market and that's where most of your decisions come from." (1:8, 10).

The other participants relate the value of DM from a perspective of their organization. The values that are supported are all related to a performance improvement. One participant argues that DM will help an organization to achieve a better performance than a competitor and that is an important objective:

"You want to become faster than your competitor, you want to make better decision than your competitor, you want to be able to offer better prices than your competitor and you want to be able to offer a better quality than your competitor. Because, these are all core values of the benefits for an organization." (2:44).

Also, another participant states that the values of DM are to be found in four different perspectives, which are transparency, maintenance, separation of concerns and the capability of being able to achieve this. Transparency is pointed out here, because it assists in bridging the gap between IT-users and business-users:

"[…] Transparency, at the same time, provides some business readability, because everyone is speaking the same language that also means that everyone, form a business user who is very capable of running a business plus all the way to the IT guy, they can both understand what they build after they built it, right." (4:6).

4.2.2 Decision Automation

As mentioned by the participants and in the theoretical review, DA is considered as an essential component in DM. The interviewers therefore asked how participants see the role of DA in regards to DM. While one participant argues that DA is not always the goal as sometimes a human decision maker is needed to effectively make a decision, the participants seem to agree that automating decisions is an imperative value in DM:

"Organizations are more and more working towards the automation of decision, because the whole world of internet transactions forces them to." (2:50).

"Automation (of decisions) I think is definitely a key, because it very much sort of proves how we can go all the way when it comes to maintenance, when it comes to model driven development." (4:21).

Generally, DM and DA are seen as separate concepts by the participants, in which it is likely that DA will be realized after DM is being implemented. This can be related to the values of DM mentioned in the previous section, because automation helps to make the same decisions in a consistent way. Also, it is argued that using DA will make an organization more agile, because changes in decisions can be implemented quickly. The interviewers followed-up on the answer and asked what important drivers for decision automation are. According to one participant, these drivers are more efficiency or cost reduction. Additionally, a supportive argument is given by a different participant, who states that the organizational part is the main purpose for automating decisions:

"[…] the organizational part is often the main goal, right. We are doing all of this so we can automate, so we can reduce costs, so we can lose headcount, use less resources. So, I think 90% of the time that was the goal (of DM), automation. […]." (4:21).

"They are forced to improve their goals such as higher efficiency or cost savings. These are the most important drivers [...] It is often obligated from the top of the organization to enhance their automated processes." (1:20, 22).

As stated by all the participants, a decision service is desired by organizations to realize values of DM. In order to do so, automatable decisions need to be discovered. The interviewers asked how the decision points are found when trying to automate decisions from non-automated decisions, as it could provide insight on the utilization and values of analytics in such process. The results suggest that there are various methods for deriving automated decisions from non-automated decisions, but that there is no consensus about the right approach of deriving automate decisions from non-automated decisions.

One participant explains that you look at the role of the human decision making and determine to what extend it can be automated or model the decisions using techniques such as DMN. The participants seem to agree on the fact that it is context or domain depended:

"[...] First that you understand and model a phenomena. Phenomena could be, something is crossing the road. Then you need to model what you are going to do and which decision are related to these activities. [...] The case is that the first definition of a phenomena should always be created manually, but the different degrees in it will be more and more automated." (2:75).

Other participants argue that it depends on the context in which decisions are to be made. The use of the DMN standard is mentioned by several participants to expose decisions that can be automated:

"[...] there is a standard defined for that, called DMN. Decision Modelling and Notation – standard. This provides an overview of how an organization can come to certain decisions. [...]." (2:56).

"[…] in order to do that (find automatable decisions), I think I would firstly establish a key principle. First is that a decision is always part of a broader process. […]." (4:28).

However, both advantages and disadvantages of the DMN standard are argued. One participant states that the DMN standard is a young notation that needs to mature and that the ability to extract decision logic, e.g. BRs, from historical data makes the use for DMN as a rule discovery tool unnecessary. On the other hand, the use of DMN provides transparency, because it outlines what the requirements for a decision are and the notation represents a language understandable by both IT-users and business-users.

Once automatable decisions are found, the next step will be to automate them. The participants have various views on how they automate decisions. Two of the participants also provided an answer with an entire step-by-step walkthrough for automating decisions from non-automated decisions. The first descriptions is similar to the theoretical explanation, identifying a decision with the use of a model notation (e.g. DMN) and automate these decisions and put these automated decisions into a decision service that is callable for organizational applications. The second participant provides a framework for automating decisions.

"[…] as a general framework to abstract executable decision from a manual process, I would firstly start at the process side of things, […] Just trying to observe what the process is. […] Secondly in this process, I would try to find my decision points […] My third step would be define the decision criteria, define how this decisions is made up. […] And then fourthly I would look at the requirements of a decision. […] then fifth is going back to the process that connects the steps to the process." (4:28).

The interviewers continued asking about the specific techniques for modelling and executing a decision service. BRs are commonly used and are executed in the Rule Engine of the BRMS. The structure and components of a BRMS differ, one of the participants explains that the components were in-house built:

"The techniques used for automating such decisions could be both with rules and tables. […]" (1:24).

"A number of different techniques. […] First of all there is a rule engine that executes automatically, […] that remains at the core, […] Around that core, there were a number of different other components in order to prove the platform that we had. One of the components was an analytical component, […] obviously there is a decision service and a whole SOA architecture around it. […]." (4:33).

Several techniques are used to automate decisions and execute decision services. Over time, these decision services need to be maintained and eventually improved. When being asked who is responsible for maintaining the automated decisions, the participants replied the following:

"The maintenance and governance is for the business of the organization, technicians/IT staff cannot maintain decisions. […] we teach people on the business side to maintain the decisions […]." (1:32).

"[…] But definitely on the business side, […] The IT staff are needed to make sure support the process in a way that all the data from systems is collected or where users are able to fill in this data in order to make a decision. But they stay out of the decision activity itself." (1:34).

"[…] it differs per project. We have not managed to find a single one fitting solution for all projects. […]That is why we try in our programs to teach capability managers to start thinking about maintenance, even before project is started. It is often that this is sort of an afterthought, let build it first and then we will see how to maintain it. You sort of have to make the case for the maintenance as well. […]." (4:37).

The maintenance and management of the decision logic may differ from project to project, but is often placed at the business side. According to one participant, the maintenance and management activities are easily forgotten when an automation project starts. It depends on the persons involved and their knowledge to determine who will take the maintenance and management responsibility.

4.2.3 Analytics

The empirical results so far concentrated around DM and the association to how decisions are to be automated. In this section the results will shift towards the use of analytics in association to DA and DM, to see how these concepts are related to each other. Together these results provide insights on how analytics add value to decision services. The first question proposed aimed to explain to what extent analytics are used for decision services.

The participants appears to have different views on how analytics are used for decision services. Depending on the field of operation of the organization, analytics are not used at all, are used to initially design decision services or provide insight on how current decision services can be improved. In some cases (predictive-) analytics are embedded to the decision service. The use and added value of analytics are considered tools to improve the logic of a decision service.

In the field of laws and regulations is not likely to use analytics for changing decision logic. This has to do with the fact that the actual logic is bound to governmental institutions. The purpose for analytics is this context is more focused on descriptive analysis.

"We do not use analytics to design our automated decisions at all. [...] The regulations describe the goal, the target group and conditions, with analytics you can identify if you meet the objective, are the conditions still justified to meet our goal? So analytics is more used as an analysis for policy." (1:36).

The other participants, who operate in a faster changing environment, argue that analytics is a component that may not be lacked. Moreover, the use of analytics is multilateral, because analytics can be used before, during and after (e.g. optimization) the design of a decision service:

"Analytics can be used in the ideation stage, before a specific decision service has been designed, to see what kind of problem might be worth building. [...] Analytics can be used as part of the decision logic design step when constructing decision services. Analytics can be used to confirm the business rules proposed by subject matter experts (e.g. to confirm that a set of rules will identify high value customers) and, over time, to suggest new rules to those subject matter experts through data mining. [...] Predictive analytics can be embedded in a decision service to allow logic in that decision service to work on probabilities not just fixed data." (3:2).

Another participant states that analytics are used in an organization that has complex decisions with huge amount of BRs, e.g. financial organizations:

"[...] the extent to which analytics is used is increasing. And where is it used most often, well it is most often used in an environment where you have to do with a lot of rules." (2:94).

"*[...] I think you are not able to design a decision environment without analytics."* (2:110).

"And then there comes the point (after implementing a business rule system) that you want to bring some intelligence from the historic data to the rules." (2:119).

Knowing that analytics are used in several ways to improve a decision service, the researchers asked about the values that come with it. First of all, analytics provide more certainty, because it gives inside to (future) possibilities of a decision. In addition accuracy and agility are mentioned as values. Certainty and accuracy are partly related to each other, since both values centers around the precision of a decision.

"The value of analytics for the automation of decisions is that analytics provides more certainty, in particular, certainty about cases of transactions which you would usually not know." (2:83).

"Generally, analytics improve accuracy. By using analytics an organization can make more fine grained, precise decisions. Analytics such as risk models or fraud models, propensity to accept models or micro-segmentation models all make it possible for a decision service to make a more targeted decision. Analytics can have a less direct effect on agility and costs also. Using analytics, and especially more adaptive self-learning analytics, can reduce the time to update the decision service to reflect new realities. While it is sometimes quicker to write new rules, sometimes analytics can pick up changes in the underlying data and respond to those changes before a human observer was really aware. This improves agility. Similarly, it can be cheaper to use an analytic algorithm to come up with say clusters or segments than it would be to have a group of SMEs do the same work." (3:4).

One participant gave an example where analytics and decision services are combined to make more effective decisions. Zalando, a webshop selling clothes spends a significant amount of money on the clothes that are being send back:

"[…] because the articles that come back need to be checked, the packing needs to be checked, eventually it needs to be disinfected, in order for the product to be sold again. So, Zalando wants an estimation on beforehand if someone is going to buy something, if they are likely to keep it or to send it back." (2:89).

In this case analytics is used to determine whether it is likely that a customer will keep the purchase or to send it back and the analytics will influence the decision logic of the webshop. Now that the use and value of analytics in decision services has been established, the interviewers asked to what extend analytics are utilized to maintain or continually improve automated decision services. The results show that analytics are used for both improvement and maintenance of a decision service. In terms of maintenance, analytics are used to provide business-users with reporting and analysis tools to determine the performance of a decision service.

"[...] In every case, analytics can be used to tie the decision outcomes to the business value of those outcomes and track decisions against their associated metrics." (3:2).

Analytics are also used to monitor the effectiveness of the decision services and provide handles to optimize and improve decision services. In terms of improvement, the participants argue that predictive analytics is utilized:

"Well, actually it is used and it becomes smarter. The moment when you want to change something in a system, it will ask you to also take a look at this and this. Things that are related to the change you make." (2:100).

Based on historical data, analytics can be used to predict future outcomes and can be integrated in the decision service. This trend of using predictive analytics is also mentioned by the participants. The interviewers continued by asking potential future trends regarding the use of analytics to enhance automated decision services:

"Changes are likely to come in two areas – the kinds of analytics being developed and the balance between analytics and explicit decision logic/business rules." (3:8).

"[...] the next trend you get is, if you search on the internet you will find predictive analytics, linear models, non-linear models and a brand new trend called forensic analytics. [...] You are going to use data elements, with a very small volume of data, to predict. This evolves to, as the Germans name it, the Fingerspitzen Gefühl." (2:123).

"So where we really start connecting machine learning and the optimization algorithms with the decision making. […] But we cannot continue to build simple rules. [...] we need to be smarter and I hope it will evolve that way." (4:48).

4.3 Summary of the results

The general view on DM is to model, maintain and execute decisions in a structured way, with the purpose to make better decisions. Common values of using DM are agility, transparency and consistency. DA results in more consistency for decision making and is considered as an imperative complement of DM. DA is not always seen in relation with DM as there are situations where a human decision maker is more effective. Overall, there is consensus about the fact that DA will happen when an organization adapts the DM approach.

DA is usually applied on operational decisions and are to be found with the help of modelling tools, e.g. DMN or analysis of historical data. Automating decisions is context dependent and often driven by increasing overall efficiency or cost savings. Automated decisions are generally maintained by business users, but might differ per project.

Analytics provides more certainty in decision making and can be used to design the initial decision services, but more commonly used to provide insight on how the decision services can be improved. The utilization of analytics embedded in decision services, especially for predicting future outcomes based on historical data, is increasing rapidly. Analytics may improve automated decision services, but the use of analytics for this purpose is not yet widely adapted.

The future perspectives include an increasing use of predictive models, to assure real-time recognition of abnormal behavior. Integrating such predictive models is the next step in connecting machine learning to decision logic for improving decision making.

5 Discussion

This section discusses empirical results from the previous chapter in order to answer the research question. Additionally, we will discuss the meanings of the empirical results in comparison to other theories and literature while using the same structure and themes that have been used throughout the research. The research was set out to discover how analytics are utilized in a decision service context and what values analytics have for decision services. Therefore the following research question was proposed:

What values, if any, do analytics provide for decision services?

5.1 Decision Management

According to Helo, Anussornnitisarn and Phusavat (2008), there is a high urge for any competitive organization to effectively manage activities within organizations. Bryd and Turner (2000) argue that agile and responsive IS play an important role in this and according to Taylor and Raden (2007), utilizing Decision Management (DM) enables such effectiveness as it centers on managing and automating daily operations to increase the organization's performance. Generally the empirical findings seem to be in line with these statements, however, DM is not just focused on monitoring daily operational decisions. A valuable aspect of DM is to effectively manage the entire decision making process. This includes describing and maintaining ways to improve such decision making, which is often based on analytics. The empirical results seem to be in agreement with Taylor (2015), claiming that the management part of DM also should ensure monitoring of the decision performance and the continuing evolvement of the decision process.

The operational decisions can be seen as the mechanisms to deliver the strategy of an organization and should therefore be monitored, controlled and optimized to enable organizations to perform as desired (Taylor & Raden, 2007). According to Fish (2012), DM provides five values, which are: more accuracy, cost reduction, latency reduction, improved consistency and an increase of agility. The empirical results show that the value of DM could be quite diverse, whereas agility and especially consistency are considered to be imperative values. The latter value, consistency, is explicitly realized with decision automation. Furthermore, DM is considered as a business capability which is accountable for developing executable decisions that simultaneously provide traceability and transparency when performing business, with the purpose to make even better decisions as time progresses. As one of the participants in our research defined it, DM is the entire process of analyzing, describing, controlling and maintaining for decision making. One of the participants argues that DM results in strengthening of the core values of any organization, as it allows an organization to make better and faster decisions than their competitors. Although the values of

DM sound promising, there are also critiques on the approach. One participant describes that the values presented by Taylor and Purchase (2016) (accuracy, consistency, cost, latency and agility), form common advantages when an organization determines to automate. For instance, the achievement of better accuracy may be deceitful, since programming an application in e.g. Phyton should also result in more accuracy. Point is, that the values mentioned in the theory may be achieved by other ways as well, therefore being fixated on the values of DM may mislead an organization. One participant argues that the DM approach is simply used to make better decisions with the goal to behave better than the competitors.

To increase consistency of decision making, an important part of DM centers on automation. As the struggle for organizations to rapidly respond to changing business environments and dealing with extensive amounts of data continues, automation of operational decision making could provide a solution for dealing with such difficulties (Taylor & Purchase, 2016). The empirical results seem to be confirming this claim, as one participant provided an example of changing and implementing a new marketing campaign. The participant argued that the use of a DM tool that automates decisions, e.g. a BRMS, allowed the organization to shorten their time-to-market marketing campaign from eight weeks to only four days. The reason why is that the rules in the BRMS that design the marketing campaign can be altered with a few tweaks and in a fast manner, which results in reducing overall costs, reducing the time to market and gaining a competitive advantage.

5.2 Decision Automation

As stated by the literature and the empirical results, Decision Automation (DA) is mainly focused on operational decision making and encapsulate these into decision services. The focus lies on operational decisions, because these decisions occur often and repeatable and require less knowledge, which makes them suitable for automation (Taylor & Raden, 2007). While several participants argued that DA is an essential part and often the goal of DM, it is also context-dependent. For tactical or strategic decision making, automation is less convenient as these decisions are more complex and have a higher impact on the organization, which is in line with the theory (Taylor & Raden, 2007). It is less likely to automate such decisions since the need for an expert human, suggestive opinion is desired. Automating operational decision making is often driven by the need to increase efficiency or reduce costs, as the results show.

Modelling automated decisions derived from non-automated decisions is done in various ways. According to Object Management Group (2016) a common way to model decisions is with the DMN standard. While the results show that the participants are all familiar with the DMN standard, the way how they automate decisions might differ. The participants use various ways to define the logic with the decision model, e.g. with BRs, decision tables and decision trees. These techniques are among the most common approaches to automate decisions as it is understandable for both business and IT staff. This statement is endorsed by the literature as it states that DMN is a general notation that is comprehensive for all kinds of users within the organization (Object Management Group, 2016). It is arguable that DMN exclusively provides the approach for exposing requirements for decisions, since analytics based on historical data could also expose these requirements. Nonetheless, using DMN provides a common language for business-users and IT-users and therefore helps to bridge a gap between these departments.

Moreover, the participants all use or implement some sort of system to manage and execute these automated decision services in order to track how the decisions are performing. This is simultaneously how analytics are commonly connected to decision services. The prevalent way of how analytics are utilized in automated decision services is by tracking the performance of the services. The maintenance of such decision services is at the business side of the organization. The responsibilities of the maintainers are, based on the analytics, to take action and alter the decision services if needed. The IT-staff supports this process by making sure that all the data is at the right place in order to make a decision. While this is the common way at the moment, it is likely that analytics will play a more extensive role in maintaining decision services. Embedding predictive analytics in decision automation could reduce the role of abstract human thinking in decision services as will be discussed in the next section.

5.3 Analytics

The gathered results show that analytics are not mandatory for designing decision services. However, the extent to which analytics are used is increasing. The true value of analytics present itself for maintaining and improving the decision services. According to the participants, applying analytics in a decision service execution will result in smarter decisions. Analytics provide insights on how specific goals are reached and what a better way is to reach such goals. According to Taylor (2009), analytics in the context of decision services are utilized in two ways: a technique to acquire and design decision services based on historical data or as a model to predict probabilities that can be integrated in the decision service's logic. The empirical results showcased multiple other values that analytics can provide in a decision service context. These values include that analytics can be used for decision logic within the decision services, but also in a less direct way to measure and confirm if e.g. a set of Business Rules (BRs) perform as intended and to even suggest new rules to improve the decision service's outcome. Other participants seem to be confirming this statement as these participants use analysis tools to consider the results of the effectiveness of the decision service and based on the results try to optimize it. According to one participant analytics integrated in a rule engine can help predict which rules should be executed first to generate the most effective path for decision making. Another participant explained that analytical models are often used by webshops to predict whether a customer is likely to keep the purchases and will not return the product. The same participant explained that such models are also used by credit card companies, to understand a customer's behavior and act when something unusual happens. In conclusion, analytics are used in a predictive manner to optimize a decision service.

According to the results objectives and conditions are often measured by the use of analytics, which results in changing automated operational decision services if necessary. This is similar to what the theory states (Selman, 2011; Russom, 2011); analytics enhances the decision making process by providing insights for new business opportunities. The utility of analytics for designing decision services might also depend on the domain it is operating in. According to the results, governmental institutions are not driven by making profits, but are driven by political views. In the private sector however, the urge for profit making is much higher and therefore the use of analytics in automatic decision services is much more valuable.

Furthermore, according to the participants, the values of analytics in a decision service context include more accuracy, certainty and a lesser effect on agility and cost reduction. As time progresses, it is likely for an organization to adapt more self-learning analytics into their decision services. According to the empirical results, using such analytics will result in reducing the time to update automated decision services that reflect the new reality. Analytics can acquire changes in the underlying data and respond to these changes significantly faster than a human entity can. Additionally, analytics and analytical algorithms utilized in a decision service context could reduce costs as it provides faster and is cheaper to use than having a team of business analyst improving the services.

Moreover, future perspectives of analytics in decision services and how analytics will continue to add value in such a context, are bittersweet. According to the empirical results, trends of analytics to enhance decision services and how analytics are integrated in such services consist a shift in the kind of analytics developed. The balance between analytics and decision logic will transform. According to Philips-Wren, Iyer, Kulkarni and Ariyachandra (2015), data driven organizations perform better as they can make more educated decisions. Analytics provide the insights for such educated decision making. However, in present time analytics augment decision services from structured data mainly. Artificial Intelligence (AI) developments enable organizations in the future to integrate such technologies in decision services, to gather information from unstructured data that would also be able to consistently update and to learn from itself. Instead of having a human factor to look at the data and determine what action need to be made, adaptive analytics is able to update itself. Such trends will also result in inconveniences as one participant points out. The fact that machine learning and similar technologies e.g. forensic and adaptive analytics will have a bigger impact in future decision making makes organizations also uncomfortable. Relying on an analytical algorithm for decision making causes organizations to be anxious, relying on technology for critical aspects for decision making could feel like a lack of control. The same participant points out that as analytics becomes more omnipresent and acquainted by organizations, the trust for such AI technologies will increase. The human factor in decision services will decrease and will limit itself to determining policies for logic, while adaptive and forensic analytics will cover the part of designing and maintaining the decision services. The value of analytics in decision services is likely to expand, withal, analytics will not be able to consider every factor for decision making. Arguably the role of human in decision services will shrink but can still be considered vital for specific cases for its subjective point of view.

6 Conclusion

The objective of the research was to discover the values of analytics in decision services. By exploring and examining how analytics contributes to add value in automated decision services, the research can add to the current IS body of knowledge as this subject has been limitedly explored. In order to obtain valuable results we conducted a qualitative study where we examined and questioned multiple participants from different organizations that either implement automated decision services or work with automated decision services on a daily basis. All for the purpose of answering the research question:

What values, if any, do analytics provide for decision services?

6.1 Implications of Findings

Decision Management (DM) is an approach that can be used to create, maintain, execute and optimize decisions. The purpose of DM is to improve the decision making of an organization. Theoretical and empirical data show that DM is focused on operational decisions and that DM centralizes around the automation of these decisions. Organizations may apply this approach for a variety of reasons, of which agility and Decision Automation (DA) are the most common ones. Decisions are likely to be automated with Business Rules (BRs) and are encapsulated in a decision service that is callable by applications in the organization. Taylor and Raden (2007) argue that operational decision making must be accurate, consistent, and agile which are executed in a cost effective way to enhance in overall effectiveness of the organization. This research showed that analytics contributes significantly to such values as it monitors the performance and provide insights on how the decision services can be improved.

This research has identified several values that analytics contribute to decision services. Before continuing to the explanation of the values, it is worth mentioning that the use of analytics are domain depended. Analytics are likely to be used in organizations who have a complex and significant amount of BRs. Results show that analytics are applied in two ways for a decision service. Either to design a decision service, to provide insights in the improvement of a decision service or both. These are the areas where analytics may add value for a decision service. When analytics are used for the design of a decision service, the focus lies on analyzing historical data to determine decision logic. If analytics are used for the improvement of a decision service, analytics may be used to monitor the performance and adjustments based on this analysis may result in improvements. An upcoming trend, which is in some cases already used, is predictive analytics that are embedded in a decision service.

The results of this research indicate that analytics add values in numerous ways. Analytics definitely adds value for decision services by improving certainty, accuracy, agility and cost reduction.

Firstly, analytics help to provide more certainty into the decision logic of all the decisions within a decision service as insights in possibilities for future realities may be predicted. In practice, analytics are used to predict whether it is likely that a customer will keep a purchase or send it back. Based on an algorithm, a customer is scored and this provides the organization with more certainty about the amount of purchases are likely to be sent back. An overall trend is that organizations use their own data to obtain information and knowledge from the data, as for instance with the use of Business Intelligence and Analytical technologies.

Secondly, accuracy is considered to be a value that analytics provide for decision services, as it helps to make more precise decisions. For instance, the use of a fraud detection model for a credit card company, will detect patterns and anomalies. Based on these patterns the model can detect if an activity is fraudulent. Accuracy, which is considered a value by both theoretical and empirical results, is improved because an organization uses analytics to determine whether an activity is abnormal or not and simultaneously base a decision on it.

Furthermore, using analytics for a decision service may contribute to the improvement of agility for the entire organization. Analytics are able to detect changes in data and may react to these changes, faster than a human eye can. A future trend will be that organizations adapt analytics that are self-learning, which can help by reducing the time for decision service updates. Agility is important in terms of the flexibility of an organization in the environment it is operating in which is where a significant amount of decisions originate from.

Finally, analytics for a decision service may have an effect on cost reduction. However, it should be stated that this is a less direct effect. Frankly, because the use of an analytical model for determining the conditions of a decision are less expensive than to have subject matter experts doing identical work. To illustrate, a grocery store wants to know what their customers are likely to buy. E.g. if a customer visits the store on Thursday, in the evening and is a male, then he is likely to buy beer. Analytical models may help to determine these conditions which will save costs otherwise spend on employees. It is rather common that automation in an organization may result in cost reduction, because work done by humans can alternatively be compassed by IT.

A future trend is likely to be that the use of predictive analytics and models shift towards real-time recognition of abnormal behavior. It is likely that the above mentioned values will increase, however, relying solely on analytics as mechanisms for decision making is currently doubtable. The integration of predictive analytics in decision services is a step closer towards the use of machine learning in improving decision making. This may jeopardize and reduce the human role in the decision making process. The importance of decisive and subjective human perspectives will shrink in future decision making as an increase of self-learning systems is inevitable.

6.2 Implications for Future Research

While the research showed that analytics can play a fundamental role in decision making, especially in context of predictive analytics and self-learning systems, the role will only become more important. Analytics will increase value for many organizations in regards to making effective, rapid and overall better decisions in an automated context. Further research in this area is therefore conducive.

Difficulties arise when the need for real-time decision making increases. Real-time decision making requires high quality analytical data. Future technologies, in regards to predictive analytics, increasingly use a larger volume of data. Further research could be extended to the use of so-called Forensic Analytics. These kinds of analytics tends to use as little data as possible to predict future outcomes. Forensic Analytics can be considered as a feasible next step to support Artificial Intelligence technologies.

Additionally, future research could also extend to DA for tactical and strategical decision making. As decision making technologies become more intelligent and the amount of data gathered increases, possibilities arise for potential automation of decisions on a higher level other than operational.

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APPENDICES

Appendix 1: Interview Guide

Introduction to the topic
Decisions are the core of any organization, it could be about accepting a customer, providing a loan, reject a claim or managing inventory, every organizations is involved in decision making on a daily basis. An increasingly important component in many successful organizational business strategies is therefore understanding, managing and automating decisions. Managing decisions may result in overall effectiveness of the organization as well as improve business outcomes.

Decision management systems are optimal for frequently occurring decisions, based on information available in an organization's Information System. However, decision management systems are not capable of learning by themselves, which means that a decision management systems acts in a way that it was originally designed for, while the macro-environment of the organization are changing. Analytics can provide insights of these changes which can play an important part in decision management systems. According to theory, decision management offers value on five different levels:

1. Accuracy
2. Consistency
3. Agility
4. Latency
5. Cost

Analytics help provide insights to what has changed as well as how organizations should react to it, grasping new business opportunities. The use of analytics in the context of Business Rules according to the theory can be two folded. Analytics can be used as a technique to acquire rules from historical data. But also, analytics can be used to create a model that predicts and enlarges the information that is used to make and improve rules.

For our research we are interested in the use and role of analytics to design and maintain decision service, and the influences of how analytics contributes to add value in automating decisions.

Interview instructions
The interview will take place with one interviewee at the time and two interviewers. The interview will be held in English and is preferably conducted via Skype. The duration of one interview is approximately 30 minutes. With permission of the interviewee, the interview is going to be recorded. A transcription of the interview will be send to the interviewee afterwards.

The interview is going to be semi-structured, which means that a number of questions are fixed and will provide a red line for the interview. Additional questions will be asked, based on the answers of the interviewee to ensure more in-depth insights.

In order to meet ethical responsibility during this interview, we will follow four principles in the interview. Each principle is outlined below:

1. **Voluntary participation and harmlessness:** the input of the interviewee for this research is voluntary and the interviewee has the freedom to stop at any moment with participating without further consequences.
2. **Anonymity and confidentiality:** each interviewee is protected in this study. Interviewees in this research will not be identified by other readers or researchers. The identity of the interviewee is not to be revealed in the report.
3. **Disclosure:** an interviewee receives introductory information regarding the research on beforehand of the interview. This basic understanding helps to determine whether or not the interviewee wishes to participate in the research.
4. **Analysis and reporting:** the collected data from the interview will be transcribed and coded. Analysis will be conducted and the results are intended to commit to the scientific community.

Introductory questions

1. Can you tell us something about your company and your position within this company?

Main part questions

The questions in the main part are divided over three themes. Each theme is related to the research question of this study.

Decision management

1. In your opinion, how would you describe decision management?
2. How would you describe the value of decision management?
3. How would you describe the role of decision automation in decision management?

Decision automation

4. Can you explain us the process of deriving automating decisions from non-automated decisions?
5. What technique(s) is/are used to automate the decision service?
6. Who is responsible for the maintenance of automated decisions?

Analytics

7. How does analytics add value to automating decisions (in regards to: agility, consistency, latency, cost, accuracy)?
8. To what extent are analytics used to determine decision logic?
9. To what extent are analytics used to adjust/maintain decision logic?

Closing questions

1. Do you have any comments you would like to add in the context of decision management, analytics or decision automation?

Appendix 2: Compilation of the Literature per Theme

Decision Services Themes	References
Decision Management	Taylor & Purchase (2016); Taylor (2013); Object Management Group (2016); Object Management Group (2017); Fish (2012); Taylor & Raden (2007); Von Halle & Goldberg (2006); Taylor (2015); Taylor (2011); Philips-Wren, Iyer, Kulkarni & Ariyachandra, (2015)
Decision Automation	Fish (2012); Cumming (2006); Taylor & Purchase (2016); Object Management Group (2016); Taylor & Raden (2007); Nelson, Rariden & Sen (2008); Meservy, Zhang, Lee & Dhaliwal (2012); Business Rule Group (2000); Von Halle & Goldberg (2006); Morgan (2002); Graham (2007); Svensson & van Biert (2014); Rosca, Greenspan & Wild (2002); Polpinij, Ghose & Dam (2015); Stineman (2009); Taylor (2005)
Analytics	Chen, Chiang & Storey (2012); Someh, Wixom, Davern & Shanks (2017); Abbasi, Sarker & Chiang (2016); Philips-Wren, Iyer, Kulkarni & Ariyachandra, (2015); Pearlson & Saunders (2004); Negash (2004); Chaudhuri, Dayal & Narasayya (2011); Işık, Jones, & Sidorova (2013); Hosack, Hall, Paradice, & Courtney (2012); Elbashir, Collier & Davern (2007); Russom (2011); Mathew (2012); Davenport (2006); Taylor & Raden (2007); Evans & Lindner (2012); Trkman, McCormack, De Oliveira & Ladeira (2010); Eckerson (2007); Watson & Wixom (2007)

Appendix 3: Transcript Interview Participant One

No.	Person	Content	Code
1.	DB	Alright, let's begin. Could you start with providing us with a short description of your function and the company you are working for?	
2.	P1	I am owner of a company called RuleManagement Group, IAM4. Two companies that are governed as one company. What we do? We develop decision services and models based on laws and regulations. We have a method and supportive tools to derive rules from such laws and regulations by analyzing and make models from it and transform it into executable services. I have a small echo by the way.	
3.	DB	Oh, maybe the sound is too loud, is this better?	
4.	P1	We'll see. The market sector where we perform our business is laws and regulations. In this very specialized market sector I would consider us market leader in The Netherlands and maybe even in the world, as there are not many companies operating in this area of expertise.	
5.	TB	Alright, let's continue to the next question. The interview is divided into three themes. The first theme is Decision Management. How would you describe DM?	
6.	P1	The whole of analyzing and making explicit, describe, maintain and control but especially organization of a process for decision making within an organization. And applying the knowledge that is important for the organization to make a decision. Which is quite broad, but most important is that you organize it as a process and not a project, where you have to deliver something to the organization. Organization is essential as it describes the tasks and responsibilities etc. for the decision making.	DMT
7.	TB	Okay, how would you describe the value of DM, for a company?	
8.	P1	The value is quite diverse.	
9.	TB	Okay	

10.	P1	As an example, we once participated in a research project on the subject of agility and flexibility for an organization. And the scientists thought it would be needed to develop an architecture to ensure agility. And I thought to myself, huh? Architecture for agility does not exist. Agility is an aspect of your architecture, in other words as an organization you should think where agility is important. Agility is important part in regards to flexibility towards the business market and that’s where most of your decisions comes from. The value can be quite diverse, another example, if I was an energy company from back in the day where decisions were quite irrelevant cost wise, but nowadays it is very important for such companies.	DMT DMV
11.	TB	Ah okay, so agility you would consider agility as a value of DM?	
12.	P1	Yes, agility is a value of DM.	DMV
13.	TB	Okay, and how would you describe the role of automating decisions within DM?	
14.	P1	That would be the decision, sometimes the sound is fading? Could you repeat the question?	
15.	TB	How would you describe the role of automating decisions within DM? Do you see it as one thing? Is it an additional value of DM?	
16.	P1	No, I see DM and decision automation as two separate things. You can see it in the way how we perform our business. It is not like if you govern your decisions, you have to automate them. It could be that you want a support expert opinion for a specific decision. It depends on the domain if you need to automate decisions and if it’s even possible. But most business cases we handle are based on automation. Usually, large administrative organizations that do a lot of repeatable decisions and that’s where automation is really important. I would describe DM as the whole process from begin product to end product, for example deriving oil from the ground. After that you have the distribution part, which can be in an automated form but could also be in the form of task description, other forms or brochures for instance. So the implementation of your decisions and rules can be multifaceted.	DMT DAN REL:DMDA

17.	DB	Is it often focusses on operational decisions?	
18.	P1	Absolutely, without a doubt. It is often focused on operational decisions. Strategic decisions you need different kind of information. Based on analytic, operational decisions can be considered in the strategic decision. But the focus is generally on operational decisions. That's where you can apply rules and fine tune the operational decisions. So we really are focused on the operational decisions.	DAN
19.	TB	How does the process or mechanism work for your company to automate decisions from non-automated decisions? How do you find these operational decisions?	
20.	P1	As I said, we operate in the market Laws and regulations	
21.	TB	Yes exactly	
22.	P1	This means that these organizations often a great deal of decisions have automated, think about the IRS or UWV (unemployment agency). Even though UWV is not that far yet with automating decisions. They are forced improve their goals such as higher efficiency or cost savings. These are the most important drivers, not strategic drivers unless you want to call that strategy. It is often obligated from the top of the organization to enhance their automated processes. Where can you do that? What is the role of people within my process and where this role can be replaced by automated decisions? And if they are law based, you can automate these decisions as long they are based on objective data. Sometimes organizations need a suggestive judgement, they need a human judgement e.g. determining if someone is unable to work. The results are percentage based and that's where a decision service can use the results. The percentage is an objective result. It all depends on the context of where the organization is performing.	DAN RDY
23.	TB	If we look at the more technical aspect, what are the techniques used to automate decisions and get such a decision service? Is it based on rules or tables?	
24.	P1	The techniques used for automating such decisions could be both with rules and tables. If you look at what we have as a representation of tools we use natural language options (SBBR), our own rule language (if, then, else, rule language), an object model where we describe characteristics of the	DAN AUT

		relation between laws and regulation. And we have a formal constraint language and natural language decision tables, these tables are basically extended if and else statements. We use decision trees and if you talk about the table techniques etc., then we are also able to use and transform the logic from our own tools into a DMN form or something similar. Because we can entirely and formally describe our rules, we are also able to execute the automated form with a hit on a button.	MOD
25.	TB	And is DMN used as a standard?	
26.	P1	It is possible, but not at this moment. Well maybe, uh no.	
27.	DB	Can you still hear us? O, the image froze for a second.	
28.	P1	I am back. Do you know a product called Blue Riq?	
29.	DB+TB	No, we do not know it.	
30.	P1	It is a Dutch product that provides a platform for case management, process management and decision management. They use DMN with a few adjustments to describe their decision logic. We will now make an export that can read this tool and transform it. We are 99.9% compliant to DMN but we don’t model DMN in our tools.	MOD
31.	TB	When you are doing a project at a company for the IRS for instance and you automate decisions, who is responsible for the maintenance of the decisions? Is this placed at the business of the organizations or the technicians or do you maintain it for these organization?	
32.	P1	The maintenance and governance is for the business of the organization, technicians/IT staff cannot maintain decisions. They can only maintain the technology where the decisions are implemented. If you do it correctly, and you have a group of people that are responsible for the maintenance, governance, analyzing and modelling etc. of the decisions logic. That would be decision logic for the operations for your organization, which is placed at the business. What we do, we teach people on the business side to maintain the decisions, while taking their level of expertise in consideration. This doesn’t mean that a lawyer have to maintain the decision on itself but can be supported by a	DAN MAI

		knowledge analyst, who is not part of the IT staff.	
33.	TB	Yes, that is also described in the theory.	
34.	P1	He must have knowledge about IT, because you want to implement the decisions also in the IT environment. So he must be able to talk about IT related subjects. But definitely on the business side, the IT staff develops a process supporting system where the decision activities are described but that’s how far as it goes. But they don’t determine what is decided. The IT staff are needed to make sure support the process in a way that all the data from systems is collected or where users are able to fill in this data in order to make a decision. But they stay out of the decision activity itself.	DAN MAI
35.	DB	As you mentioned before, you look at the role of the human to determine to automate decisions, to what extent are analytics used for automating decisions?	
36.	P1	We do not use analytics to design our automated decisions it at all. The source is at the laws and regulations. The learn circle where you can apply analytics is much larger, which is for policy analysis. The government develops policy with a certain objective. The regulations describe the goal, the target group and conditions, with analytics you can identify if you meet the objective, are the conditions still justified to meet our goal? So analytics is more used as an analysis for policy.	ANS
37.	DB	So analytics is more commonly used for maintenance and adjustment for automating decisions?	
38.	P1	Yes analytics is more commonly used for maintenance and adjustment for automating decisions, but that’s a cycle determined by the government in our sector. It is different if you operate in the telecommunication market, for example if you talk about the acceptance of customers then this learn circle can be applied within your own organization. We operate in a sector where organizations can determine the role of policy but is in a way restricted to governmental policies. The role of analytics is therefore also limited.	ANS
39.	TB	The example you just gave, for some decisions there needs to be a human judgement to play a role in the decision making, isn’t that where analytics can play a role based on historical data to give a prediction about the future instead having a	

		human role for the decision making?	
40.	P1	Could you repeat the question? The sound is not so good at the moment.	
41.	TB	You just gave an example that some decisions are subjective judgements where a human judgement is necessary. Isn't that where analytics can play an important role?	
42.	P1	Yes, but analytics are difficult because if you want to avoid goal reasoning. You have to avoid to go the direction, just because the analytics points you to that direction. You should always consider all the factors when using analytics to determine the real reason to go a certain direction. Will this prediction really occur? Which is partially based on your assumptions, you can't consider every factor within your analytics. But if you're talking about the more suggestive decisions, analytics could play a really important role in it. But I have not seen it yet, but it will happen definitely in the oncoming years! That will happen within the context where we perform our business, laws and regulations. If analytics show outcomes where the amount of people that are unable to be employed would lead to zero percentage, then the government would intervene.	ANS
43.	TB	Alright, do you have anything to add to the contexts of decision management, decision automation or analytics that have not been discussed during this interview?	
44.	P1	Our company is named rule management group, so we did not talk about decisions yet, but I think decision management is a better term for it. For projects they often focus on the connection between process models and rule models. But rules are not models. Rules are artifacts within a model. Therefore it is good to talk about decision models, as they contain rules just like there are rules in process models. Just as in data models. So you have every kind of rules within different kind of models. When you are determining rules you always look at the decision it needs to make. Which describes the context of rules within such models.	DMT
45.	DB	Alright, I would like to thank you for this interview today. Last question, do you know any other companies we can approach for an interview as we received very little response of companies so far?	

46.	P1	Do you have a list of companies you have approached so far?	
47.	DB	We approached Achmea, IRS, UWV, Nationale Nederlanden and Rijksoverheid	
48.	P1	Sure, I will look into it, but I am more of the government side rather than the commercial side of business.	

Appendix 4: Transcript Interview Participant Two

No.	Person	Content	Code
1.	TB	Alright, we are going to start with the first question. Can you tell us something about your company and your position within the company?	
2.	P2	Okay, well Supergraph is an, alright let me first start with an introduction about the name of the company. The name Supergraph is derived from the theory of Graph, which you are most probably familiar with. I have chosen this name, because I am absolutely convinced that in approximately five years Graph databases will be as important as Oracle databases five years ago.	
3.	DB	Okay	
4.	P2	But that is my personal opinion, we shall see. Supergraph is founded three years ago in cooperation with the University of Leiden, Liacs, also our research advisor is professor Thomas Bäck of the Liacs and he is responsible for natural computing and the faculty. I have a background in applying complex mathematics for 20 or 30 years. I have been with the introduction of the Monte Carlo simulation, does that ring a bell for you guys?	
5.	DB	No, not really.	
6.	P2	Sorry?	
7.	TB	No, we are not familiar with the Monte Carlo simulation.	
8.	P2	Well, the Monte Carlo simulation is commonly used by banks to predict their maximal loss for the upcoming 24 hours. The simulation is based on ten thousand disaster scenarios and then for each scenario the impact on the current transactions will be calculated.	ANS
9.	DB	Okay.	
10.	P2	This is mainly used in wholesale banking, but to give you guys an idea. In 2001, I have had a conversation with the former chief risk officer of Fannie Mae in the US. Fannie Mae is one of the two mortgage granting organizations that went down	

		during the credit crisis. I asked him why they did not use the Monte Carlo simulation.	
11.	DB	Yes.	
12.	P2	He replied that they actually did the simulation and I asked him how often they used it. Once a month he said and I asked him why only once a month, because you should do it on a daily basis. They said that they wanted to, but that their programs run for a week.	
13.	DB	Yes and where are these scenarios based on?	
14.	P2	Those are generated randomly.	
15.	DB	Okay, from historical data?	
16.	P2	No, this is fully random. There are a few input parameters, which can be chosen and maximal and minimal values are determined, and then the computer runs the scenarios.	ANS
17.	DB	Okay.	
18.	P2	The final results is that one can predict for 99.8% sure what the total loss of a bank for the next 24 hours would be.	
19.	DB	Ah, okay.	
20.	TB	That sounds like valuable information.	
21.	P2	Yes, and it is still applied nowadays. They call it market risk, because the Dollar may collapse or a war can start in for instance, China or North Korea. All kinds of scenarios such as these are taken into account.	
22.	DB	Okay, a bit like doom scenarios?	
23.	P2	Yes and then study the impact of it. Because you know what a banks is and how it works. Basically, a bank is like a warehouse in which stacks of money and each stack has a label with its own interest percentage. The bank survive, because they buy something against two percent and sells it for three percent.	
24.	DB	Right.	

25.	P2	Yes, and that is basically what it is all about. Back in the days when ABN AMRO was still a major player, they had to adjust their money warehouse for 60.000 times a day. So, this means that 60.000 times a day the risks related to a transaction were calculated.	
26.	DB	Okay, that sounds interesting.	
27.	P2	And this is actually the precursor of predictive analytics as we know it nowadays. Besides, a second trend stood up around the phenomena of credit cards. Because people can easily use credit cards for fraudulent purposes. You have, when you purchase with a credit card, approximately eight seconds to decide whether you accept the transaction or not, and if the transaction is accepted, it cannot be undone.	
28.	DB	No.	
29.	P2	So, you need to know with certainty within eight seconds if a transaction is fraudulent or not. This is the challenge we face nowadays. To get back, the role of Supergraph in this context is to design innovative models.	
30.	DB	Right, so Supergraph tries to integrate analytics with automated decisions?	
31.	P2	Exactly.	
32.	DB	Interesting.	
33.	P2	That is what usually happens at the organizations.	
34	TB	Okay.	
35.	P2	At the moment, we are working with a car repair agency, to predict what the risk of damage would be for a specific customer. So, for instance, if a customer is insured at the agency, what are the odds that this customer will have damage in 2018? Based on these predictions, the agency can calculate the insurance rate for this specific customer. It is a decision for the insurance agency to determine what kind of insurance policies are offered when a customer extends his contract.	ANS REL:DMAN
36.	DB	Right, interesting.	
37.	TB	Is your organization also involved in the automation of	

		decisions or the management of decisions?	
38.	P2	Yes, that would be a next step. At least we offer it to our customers. We have a partnership with Decision First, in the US, who offer a tool, Decision Modeler. Which can be used to model decision autonomously.	MOD
39.	TB	Yes, we are familiar with the tool. In your opinion, how would you describe decision management?	
40.	P2	Decision Management is basically the administration of organizational decisions on a structured, documented and modelled way. Which makes it possible to automate decisions.	DMT DAN
41.	TB	Does decision management have the purpose to automate decisions?	
42.	P2	Well, decision management has the purpose to make better decisions.	DMT
43.	TB	Alright, and what would be the value of decision management? That decision are made in a better way?	
44.	P2	The results of decision management is actually that one will become better than his competitor. That is what it is basically all about. You want to become faster than your competitor, you want to make better decision than your competitor, you want to be able to offer better prices than your competitor and you want to be able to offer a better quality than your competitor. Because, these are all core values of the benefits for an organizations.	DMT DMV
45.	TB	Okay, and how would you describe the role of decision automation in decision management?	
46.	P2	Sorry, can you say that again?	
47.	TB	Well the role of decision automation, automating decisions.	
48.	P2	Yes.	
49.	TB	What kind of role this plays within decision management as a whole, related to the values you just mentioned?	
50.	P2	Well, the thing you are looking for as an organization is to find a way in which decision are made in the most consistent way. A large part of this will be realized by automating decisions.	DMT

		Because, then can be fixed, on beforehand what a decision would under certain circumstances. Are organizations more and more working towards the automation of decisions, because the whole world of internet transactions forces them to. I can give an example, a decade ago when I wanted to book a flight, I called the KLM to ask for the price of a flight from Amsterdam to New York. The KLM then told me a certain amount and I then asked how many points it would costs if I wanted to pay with frequent flyer points. Then they said it will cost you 20.000 points, but when I went to their website to looks how many points I needed to pay the flight, it said 30.000 points. In other words, the prices of a flight depended on the sales channel.	DAN REL:DMDA
51.	TB	Okay.	
52.	P2	That is still something organizations face today and then you know that these organizations face difficulties with decision management. Because decision management enable an organization to have the same pricing strategy among all the sales channels.	DMT DMV
53.	DB	So it would be consistent among all channels?	
54.	P2	Yes, exactly.	
55.	TB	Okay, and how can decisions, like in the KLM process, be exposed as decision that can be automated? Is there a method available for that?	
56.	P2	Yes, there is a standard defined for that, called DMN. Decision Modelling and Notation – standard. This provides an overview of how an organization can come to certain decisions. But, it requires a lot of consultancy work, because you need to discuss and determined what needs to be done with users from different departments.	DAN MOD
57.	TB	Right, to picture the process and subsequently to find the decision points.	
58.	P2	Yes, but it is not only the process. I think that the role and importance of a process will decrease more and more. If you take for instance, the process of an internet transaction, you can barely name it a process, because it are two mouse clicks and you are done. Processes, the workflow, are important, but in ever smaller sizes. The workflow is necessary because of	DMT DAN

		the manual decision, and those take too much time. If the whole decision making is automated, everything will happen in real time.	
59.	TB	Yes.	
60.	DB	Yes.	
61.	TB	Yes, yes.	
62.	DB	Do you that it will shift more and more into that direction?	
63.	P2	Yes, I expect it to be. There are signals that point in this direction, because decision making is one of the five components of artificial intelligence. There is analytics, forensics, decision making, the storage of the information and you have the ranking of all the available information to reach a better decision. For instance, the development of self-driving cars basically uses software for decision making based on facts and the analytical estimation if something is important or not.	DMT ANS
64.	DB	Yes.	
65.	P2	And most of the current vehicles are not yet ready for driving autonomous. Which is evidenced by the fact that some cars will use the automatic break without any assignable reason, while it turned out that it had to do with a bird flying by before the car afterwards.	
66.	TB	Yes, and the logic that is used to make such a decisions. For example the self-driving car who uses the breaks automatically. There must be some kind of logic that determines whether a car should use the break or not. What kind of techniques is used for that?	DMT
67.	P2	That is basically done by decision management.	DMT
68.	TB	Exactly, but is that determined by business rules, algorithm or a model?	
69.	P2	Well, it is based on a combination of those. An algorithm, does, well, alright we are going this direction. We take one step back. One you have a lot of historical data, and data generated by a self-driving car is historical data, and then analytics is used to determine trends and patterns in that dataset. In other words, what is normal and what is abnormal.	ANS AUT

70.	TB	Yes.	
71.	P2	And do I know what this abnormality is or not? Can I make an estimation of this or not? These are activities you will do on beforehand to get a frame of reference of the characteristics of signals which should be dealt with. And thereafter decision modeler is used to model the action you are going to do.	
72.	DB	Right, but that happens manually I assume. There is not any self-learning software program that recognizes where to pay attention to?	
73.	P2	That is something which is in development nowadays. That those activities of recognition will happen automatically.	
74.	TB	You say that the activities that need be done at the moment of a decision, will be exactly modelled. And just that very thing, which determine what needs to happen, does that involve an analytical model?	
75.	P2	Well, there are two perspectives. First, that you understand and model a phenomena. Phenomena could be, something is crossing the road. Then you need to model what you are going to do and which decision are related to these activities. Decision are intervene or not intervene, go aside or not go aside, use the breaks or not use the breaks, that kind of activities. The case is that the first definition of a phenomena should always be created manually, but the different degrees in it will be more and more automated. Which means that it will be automatically learnt. The technique for doing so is not new, it is already there nowadays. For instance, you can recognize it with credit card fraud. The analytical models used are adaptive and generate new rules which are applied on the incoming transactions. Does that sound understandable or did you guys lost me?	DMT DAN ANS
76.	TB	No, no, yes it is clear for us.	
77.	DB	Sure.	
78.	P2	Okay. Basically you should see as the credit card company who creates a fingerprint of its customer. A simple example, back in the days when I flew a lot, I always went to Schiphol by car and parked the car in the parking lot at the airport and paid with my credit card. Then, if I arrived at Madrid, I went to the Hilton and again used my credit card etcetera. But it also	ANS REL:DMAN

		happened that had to go abroad for two weeks, and parking my car at the airport for two weeks was quite expensive, so then I took a taxi. I always paid the taxi with cash and if I then arrived at Stockholm and went to my hotel for a check-in, you could tell for sure that American Express gave a call, because I had not parked my car at Schiphol, so how could I be in Stockholm.	
79.	TB	Haha yes.	
80.	DB	Yes, exactly.	
81.	P2	Those are exactly fingerprint likely detections. Because, the whole credit card company knows what I am doing with my credit card. It literally works outstanding. Once I experienced it when I was on vacation in Curacao and my credit card got skimmed, I paid my dinner when it got skimmed and the next day I paid my breakfast with my credit card and in the evening I flew back to Amsterdam and bought tax free articles in the plane with my credit card and when I arrived home I got the bank on the phone and they told me that my credit card got skimmed. I said how and when did that happen and they told me in the last twenty-four hours. They tried to buy a television, which was declined, they also tried to buy tools, which was also declined and something was bought on the airport, which was accepted. So they know precisely what you are doing.	ANS REL:DMAN
82.	DB	Yes, exactly. Very interesting, but can also you describe what the value of analytics is for decision automation?	
83.	P2	The value of analytics for the automation of decisions is that analytics provides more certainty, in particular, certainty about cases of transactions which you would usually not know. If I only take a look at the transaction, then I won’t know if it belong to the fingerprint of the user, I also don’t know whether this trick is used before or not. What now happens, for instance, do you know Zalando?	ANS
84.	DB	Yes, I do.	
85.	P2	It is an online shop where you can buy shoes and clothes and the biggest problem of Zalando is that 70% of the articles the sell is send back.	

86.	DB	Oh.	
87.	P2	This means that people buy something online, because they are too lazy to go to the store. Then it arrives home and they try the clothes and recon that it does not fit and then they send it back.	
88.	DB	Alright, yes.	
89.	P2	That costs a fortune, because the articles that come back need to be checked, the packing needs to be checked, eventually it needs to be disinfected, in order for the product to be sold again. So, Zalando wants an estimation on beforehand if someone is going to buy something, if they are likely to keep it or to send it back. And especially in the Netherlands, there are a lot of students, who buy something online and wear it on a party, wash it at home and then send it back.	ANS REL:DMAN
90.	DB	Yes, we also know that people.	
91.	P2	Yes, haha. I mean it is a typical Dutch trick and it happens a lot. Wehkamp has a lot of struggles with it and has now a model with which they can predict whether someone is going to send something back or not.	ANS
92.	DB	Okay, yes interesting and in what way are analytics used for the design of decision logic?	
93.	TB	Because, as you are describing it right now, it can assume that.	
94.	P2	Okay, the extent to which analytics is used is increasing. And where is it used most often, well it is most often used in an environment where you have to do with a lot of rules.	ANS DAN
95.	DB	Right.	
96.	P2	To give you guys an idea, I once did a project for ABN AMRO, when it still was a big organization by the way, about automating the general ledger and for the general ledger ABN AMRO has 150.000 rules. You might see it coming, but if you are going to apply each rule one by one then it does not matter whether you have the biggest mainframe of the city, you are not going to get it done. So you need to optimize and predict which rules need to be executed first in order to make as effective as possible a decision. This is part of the umbrella of decision optimization. Vito is one of the organizations who is	REL:DMAN

		working with this, but there are more. IBM does it as well, so if you have entered the rules, then the rule engine is going to optimize which rules he is going to execute first.	
97.	DB	And the rules itself, are they based on data?	
98.	P2	That would be possible yes. For the detection of fraud, for instance, are the rules based on data.	
99.	DB	And the maintenance of this decision logic etcetera. Till what extent is analytics used for that?	
100.	P2	Let me think, right now, not so much. Well, actually it is used and it becomes more and more smart. The moment when you want to change something in a system, it will ask you to also take a look at this and this. Things that are related to the change you make.	MAI
101.	DB	But those are only predictive analytics?	
102.	P2	Yes.	
103.	DB	Okay.	
104.	P2	So, it is increasingly more used.	
105.	TB	And is it also used to improve current rules and to alter current rules?	
106.	P2	I am thinking about an example, but I cannot find it. But that will undoubtedly happen.	
107.	TB	Okay, we are almost done with the questions. We would like to ask if you want to add something to the context of decision management and analytics for decision automation.	
108.	P2	Sorry, the signal got lost, for the automation of what?	
109.	TB	If you want to add something about the use of analytics for decision automation or your opinion about the future trends.	
110.	P2	I think there are two units. I think you are not able to design a decision environment without analytics. I also think the difference with decision management, the difference between decision management and business rules management is analytics	ANS DMT DAN

111.	TB	Okay.	
112.	DB	Why do you think so?	
113.	P2	Well, because you have a series of rules that results in a decision. But some of those rules will for sure be related to something you, historically seen, already know. That is where analytics comes around the corner.	REL:DMAN
114.	DB	Right, but why does that differ with the other, the rule and this description?	
115.	P2	The whole development around artificial intelligence has basically started at the beginning of the nineties. Those were systems with hard coded software. Quite fast people figured out that the environment was changing faster than they could keep up. Then artificial intelligence slowly got out of the picture. Besides, there has been a development of business rules management, because it would make the maintenance of application much easier. I had a customer in England who was a new founded bank, called EGG, and they had a very aggressive marketing campaign in which they had certain promotions. For instance, if one took a credit card at EGG, you got 10 percent of all your purchases as a Christmas present. All these kind of promotions. But their strength was that if competitors were following, they could have a new strategy within a month. Before they started with business rules, it took six to eight weeks to implement new rules for the marketing campaign. That was totally unacceptable, because that had to be faster and with a business rules management environment it took only four day to implement and to make it ready for use.	DMT DAN AUT
116.	DB	Yes.	
117.	P2	It went back from eight week to four days. The actually change in time for the business rules was only half a day, and the remaining was regression testing and check which banks are obligated to do.	
118.	TB	Okay.	
119.	P2	So, that is business rules. And then there comes the point that you want to bring some intelligence from the history to the rules.	ANS AUT

120.	DB	Yes.	
121.	P2	And then the whole concept of statistical analytics has been arisen.	
122.	DB	Yes, super. Excellent examples. I becomes more and more clear now.	
123.	P2	This is how all the things are related to each other and the next trend you get is, if you search on the internet you will find predictive analytics, linear models, non-linear models and a brand new trend called forensic analytics. And forensic analytics originates from the field of forensic investigation, also known as crime investigation. With a crime investigation it happens that you don't have any data and nevertheless tries to predict something. You are going to use data elements, with a very small volume of data, to predict. This evolves to, as the Germans name it, the Fingerspitzen gefühl.	ANS
124.	TB	Haha, yes.	
125.	P2	The feeling that something is not right. We do not know what, but we have the feeling that something is wrong.	
126.	DB	And to what extent does that differ with predictive analytics? Is that a whole different area?	
127.	P2	It is a whole different approach, because the certainty is way lower.	
128.	DB	Okay.	
129.	P2	But you should have it as starting point. First you have business rules, laws and regulations you need to follow, secondly there is the statistical part, so you are using the historically perspective to find out what you can know based on historical data. The third aspect, to get more certainty, is to build this Fingerspitzen gefühl. And if you bring these three in relation with each other, you will slowly get to artificial intelligence	DAN DMT ANS
130.	DB	Okay.	
131.	P2	And if you connect this to why the theory of graph is so important in this context. Well, if you connect this to the theory of graph, with graph you capture the statistical value or	ANS

		the Fingerspitzen gefühl of a transaction. So, if you get the same transaction a half year later, you will recognize it in real time, without conducting all the analytics.	
132.	DB	Yes, that sounds like an ideal world. Interesting.	
133.	P2	Take a look at the Graph databases who are available at this moment. The best one would be the NEO4J, you know it?	
134.	DB	No.	
135.	P2	You can Google search it, as a student you are able to use it for free. I also have PowerPoint slide for you, just a second, I can send it through Skype. I cannot find it.	
136.	DB	No, problem. If you find it later, you could maybe send it to us. That would be fine as well. Then I want to say that we have been through all the questions and we would like to thank you for the interview. You really gave us valuable data for our study.	
137.	TB	Especially all the examples you gave.	
138.	DB	Yes. Excellent examples and we will continue with the things you have said.	
139.	P2	I found the PowerPoint slides of Graph. It was a meetup in Amsterdam with this presentation, so I will send it though the chat box of Skype.	
140.	DB	Yes, that’s fine.	
141.	P2	You should have it right now. It also contains some use cases of Graph which explain the use of it.	
142.	DB	Alright, yes I got it. We are going to use.	
143.	P2	If you guys have any questions about, just let me know and we can chat about it. I really find it fascinating, the Graph databases, mind-blowing as the Americans would say.	
144.	DB	Alright, thanks again and we will assure to transcribe the interview and send you a copy of it and you may also receive the results of the research, if you are interested in it.	
145.	P2	Yes, please.	

146.	DB	We will keep in touch.	
147.	P2	If there raise any question, do not hesitate to contact me. Guys, good luck!	
148.	DB	You too.	
149.	TB	Thank you.	
150.	P2	Goodbye.	

Appendix 5: Transcript Interview Participant Three

No.	Person	Content	Code
1.	DB	What role has analytics in the design and/or maintenance of decision services?	
2.	P3	Analytics can affect the design of decision services in three ways: Analytics can be used in the ideation stage, before a specific decision service has been designed, to see what kind of problem might be worth building. Many decisions seem to be good candidates but affect too small a number of customers or have too marginal a benefit to be worth developing decision services for them. Investigative analytics can be useful in confirming the scope or value proposition of a decision services project. Analytics can be used as part of the decision logic design step when constructing decision services. Analytics can be used to confirm the business rules proposed by subject matter experts (e.g. to confirm that a set of rules will identify high value customers) and, over time, to suggest new rules to those subject matter experts through data mining. Association rules, decision trees, classification and clustering techniques can all identify potential decision rules and it is often easier to get business support for implementing these explicitly rather than using a black-box analytic model. Predictive analytics can be embedded in a decision service to allow logic in that decision service to work on probabilities not just fixed data. These analytics can be developed against structured data – a typical score such as a risk score for instance – or using newer techniques against less structured data – identifying how likely it is that a particular image contains visual evidence of a certain kind or predicting the tone of text. In every case, the decision service is developed to leverage this probability in its logic to make a more nuanced decision. Analytics can also be used in the maintenance of decision services. This mostly involves providing reporting and analysis tools to consider the results and effectiveness of the decision service. When decision services implement	ANS REL:DAAN MAI

		champion/challenger or A/B testing, analytics are important for assessing which approaches are working best. For decision services involving analytic models, analytics can be used to see if the models have aged to the point where they should be re-evaluated (assuming they are not adaptive analytic models based on machine learning algorithms). In every case, analytics can be used to tie the decision outcomes to the business value of those outcomes and track decisions against their associated metrics.	
3.	DB	How does analytics add value to decision services (e.g. adds to accuracy, consistency or agility and reduces latency or costs)?	
4.	P3	Generally, analytics improve accuracy. By using analytics an organization can make more fine grained, precise decisions. Analytics such as risk models or fraud models, propensity to accept models or micro-segmentation models all make it possible for a decision service to make a more targeted decision. Analytics can have a less direct effect on agility and costs also. Using analytics, and especially more adaptive self-learning analytics, can reduce the time to update the decision service to reflect new realities. While it is sometimes quicker to write new rules, sometimes analytics can pick up changes in the underlying data and respond to those changes before a human observer was really aware. This improves agility. Similarly, it can be cheaper to use an analytic algorithm to come up with say clusters or segments than it would be to have a group of SMEs do the same work.	ANS DMV
5.	DB	Could you describe the process of how automated decisions are derived from non-automated decisions?	
6.	P3	This is a broad topic and not one conducive to a short answer. Generally, the best approach is to: Identify very clearly the decision involved and model it using a standard decision modelling notation such as DMN. Use this decision model to identify the most obvious paths through the decision – the outcomes everyone agrees on – and automate these. Put the resulting decision service immediately before the manual decision, using it to route some transactions around the manual decision because the outcome is clear. Review all the manual transactions to see if there are groups or patterns that can be automated, adding rules and analytics as necessary. Often this involves replacing a visualization used by	DAN MOD

		a person with a score or executable analytic. Over time the decision service will handle an increasing percentage of the transactions. Generally this is an S-curve – it starts slow (because an organization is paranoid about automation), accelerates in the middle (once there is confidence and while there are still easy cases to automated) and then slows as the final transactions must be handled (these are the rare corner cases).	
7.	DB	What role will analytics have in the future for the design of decision services?	
8.	P3	The roles described above will likely remain fairly constant moving forward. Changes are likely to come in two areas – the kinds of analytics being developed and the balance between analytics and explicit decision logic/business rules: Most decision services using analytics today are using a score derived from structured data. For instance, a credit risk score or a propensity to buy score. In the future, more analytics based on cognitive/AI technologies are likely (what is the tone of this email, is this person in this photo) as are more machine learning/adaptive analytics that will constantly update themselves, learn, rather than need to be manually updated by an analytics team. Many organizations are still uncomfortable handing over critical elements of their decision making to algorithms. This means that using analytics to verify business rules or to come up with candidate business rules is often more acceptable to the organization. As analytics becomes ever more pervasive, and as companies become more familiar with analytics, this can be expected to change. There will continue to be a need for policy and regulatory logic to be added but “best practices” or “expertise” will increasingly be replaced by analytics rather than encoded in rules	ANS

Appendix 6: Transcript Interview Participant Four

No.	Person	Content	Code
1.	TB	The interview is divided into three parts and we are going to start with the first part about Decision Management. In your opinion, how would describe Decision Management.	
2.	P4	I would describe decision management as a business capability that is mainly responsible for delivering change by developing “executable” decision artefacts that subsequently provide transparency, traceability for business making. There is a lot in that. First of all, maybe to highlight the executable part. A lot of DMN practitioners say there is a twofold goal in capability, on one side there is the requirements definition. This could be almost a fancy picture describing what a decision is and then using that as a requirement for your business solution, but on the other hand, and, that is a very strong part I would say, is the executable part, where your picture is becoming what you will be running with code. I think we will see some of the transparency and traceability stuff on the other questions, I’ll come back to that.	DMT
3.	TB	Alright, would you say that the execution part, is that part of Decision Management	
4.	P4	Yes, and I think this was major component in the organization that I was part of. People were often directly looking at the executable stuff. So they would come up to me and say: we going to run this project and we going to build this decision, when can you built it? It was all about built me the executable model, because that’s going to automate the task I usually did manually by typing in a value or correcting a value or checking a value. So it was often that, as soon as we said 'decision management' it was about execution of decisions. That was the only focus they had. I would want to balance that and say there are two parts: the requirements gathering part plus the executable side and they are both key components to decision management.	DAN DMT
5.	TB	Alright, good. How would you describe the value of Decision Management?	
6.	P4	I would describe the value of Decision Management from a couple of different perspectives. These perspectives are sort of	DMT

		understood and proved throughout different projects in the organization I was part of. First of all is transparency. Transparency that both process and decision management give for organizations. First of all, it is about a common language. We are now both talking about the same thing, when we talk about something. Often in a project there is a lot of different people involved, with their own agendas and own views on how the world should work, right? The technical person comes at it [from a technical angle and] as soon as he hears a business problem he starts writing stuff down right away, for blue prints for applications. That makes it very difficult to communicate some times and you almost want to expect, often organizations do expect their project managers to be the 'all trick pony' that can talk with anyone, but even language is limited to some extent. So the notations BPMN and DMN both give a common language, so that we can start to talking about how we want to arrive at a certain decision and how do we want to process, or sequence of events that we need to conduct with a particular artefact that is going through the process. Transparency, at the same time, provides some business readability, because everyone is speaking the same language that also means that everyone, from a business user who is very capable of running a business, all the way to the IT guy, they can both understand what they build it and after the built it, right. And this is another key thing in IT and change management generally. As soon as you built something, that is going to cost something to maintain and makes sure that whenever things in the environment around it will change, that things are updated and the behavior of the system remains in-synced with where the business wants to go. So another sub-component of transparency is making sure, post-go-live and the post-development of the whole applications, you can still understand what the system is doing and how they can update it.	DMV
7.	DB	Yeah, alright.	
8.	TB	Okay, makes sense.	
9.	P4	Which is a sort of a nice segway in the second main component of the values of decision management, the maintenance part of it. We have seen throughout a number of projects that given some training and given some governance and structure, where maintenance is sort of safe and people cannot break systems, so they are not falling over in a heap,	DMT DMV MAI

		because of changes. Maintenance does empower the business to change those things that need to change often, they can change quite frequently and quite quickly, because it can because of the common language. And a rule and a table is easy to interpret, quite quickly to read, and natural to read, because of the order and things like that. So, that does help the business to control more what they, or how they run the organization. It comes back to a nice saying you often hear in big organizations, which is: do you want your organization to run your systems or do you want your systems to run your organization? And you want the first part of that. You want your organization with your organizational goals, business goal and business strategy to say OK, I you need the systems to behave like this on this new product, because I'm delivering this new product in the market, in a week, I don’t have three months for the IT-department to figure out how to launch this product from an IT perspective. That is really the maintenance part of it.	
10.	TB	That is very clear.	
11.	P4	A third one is an IT principle, called separation of concern. What I think is really nice in the notation and you sometimes miss it a bit on the process side, unless you have a really good process architect, is that in the notation itself you naturally start thinking about what are the major concerns that I want to apply in a decision; really on a detailed level, even in a single model you start thinking about how am I making a decision. It is such a decision that is locked in my head, I do it every day. But then you start thinking about stuff, and thinking about what I actually do. Criteria and how can I potentially automate something, there is a stricter thinking about what should we separate and what should we put where. Especially if you start designing the business solutions with process and decision in mind. You start appreciating the smaller things of the business as well, something, I think James Taylor calls micro decisions. Decisions that we take for granted or steps in a process you take for granted, because you do them on a daily basis. But often you see that there is a lot of risk in those things. Especially in the financial industry, a lot of small steps introduce a lot of risk for the outcome of the process. These notations and especially decision management, when it comes to decisions, stimulate people to start thinking about how it all works in all detail and then how do we design and how do we separate the different components that we are working on in	DMT DMV

		particular business process.	
12.	TB	Okay.	
13.	P4	And lastly I think, I would wrap that up as the last value proponent of the capability. I have seen it function as a real strong bridge between business and IT. IT still has a component in decision management. You get decision services and all the SOA based architecture, to make sure rule engines work and application connect apps to decision services through API's. So there is still whole technical world in decision management for IT people to fulfill. But on the flip side it is very much the business that has a very strong position in it, because in business decision management is there, it is how the business wants to translate a particular decision and how they want to go from general business knowledge that they have, to business logic to executable business logic and that is really a journey that they can control and keep controlling over time, not just with the project, but also with post-go-live and in maintenance scenarios.	REL:DMDA DMV
14.	TB	Alright, that is very clear.	
15.	DB	Yeah, clear examples.	
16.	P4	Is there any particular part that you want me to zoom-in on, or is it quite clear?	
17.	TB	Yeah, it sounds very clear for me.	
18.	DB	Yeah.	
19.	P4	Okay.	
20.	TB	We move on, can you describe the role of decision automation in decision management?	
21.	P4	Yes, sure. I think like I said in one the previous questions, the executable part is often the main goal, right. We are doing all of this so we can automate, so we can reduce costs, so we can lose headcount, use less resources. So, I think 90% of the time that was the goal, automation. Automation I think is definitely a key, because it very much, sort of, proves how we can go all the way when it comes to model driven development. It is not just a picture on a slide that someone has up on his screen and then he is going to be coding on the other screen. So, I think	DAN

		the automation peace will remain a key part in capability, especially to prove that it is such a powerful capability that can bridge business and IT.	
22.	TB	And would could be the goal of an organization if they are decision management, but not decision automation?	
23.	P4	There is still benefit. But I think you would automatically limit the benefit you get from it. It is the same thing as applying process management in your organization without really automating the processes. For example, you and I are both process architects, we go into an organization or manufacturing line and we stand there with our clipboards and our notes and our timers and we say this step takes 5 seconds, this step takes 10 seconds, what if we switch this around or train this guy to also do both steps, then it will be 7 seconds, so we have improved the process. But your improvement is limited, right? Because you remain with the same resources, the same context, you are not sort of thinking outside the box, thinking about how could we completely, from holistic view re-design or re-engineer these processes. It is the same with decision management in that sense, if you not automate it, you now have a documentation piece or piece of reference to train people or to say this is how you should take a decision, but [you can] still cannot systematically control anything because it is still a human that says: I need to consider these three criteria, well today I am going skip these two and just going to focus on this one, because that is relevant and that is the quickest way. So, you are limiting yourself.	DMV DAN
24.	DB	So, they should go hand-in-hand, decision automation and decision management?	DMT DAN
25.	P4	Correct.	
26.	DB	Okay.	
27.	TB	Alright, we moving on to the second part of the interview. It is about decision automation. And the first question we have is, can explain the process of deriving automated decisions from non-automated decisions?	
28.	P4	Right, so in order to do that, I think I would firstly establish a key principle. First is that a decision is always part of a broader process. So if I want to derive something I often need	DMT

		to look at the context of a decision and an easy way of doing that is, ask what is the process? Where does this decision sit? And often that is more processes, so up and down the whole value chain of an organization, maybe you make a certain discount decision when you onboard a new client, maybe it is a very high valuable client and you give him some discount on his first offer, but it could also be down the line when the client is closing his account and you still want to give him some discount, because you want to retain the client. Some of decisions, like 'determine discount', which is a very silly simple example, could be applied in a lot of different contexts and it depends on where you project is and what you are trying to change. So, decision always have a particular context in a process, but secondly, this is what I may came up with, but I don't know how many in the industry would agree with me on this one. But you often run a process with a particular objective and if the decision is part of the process, the process sort of only exists to reach a certain end-goal. So, to me these two principles are equally important, you have a decision in a context, but you also have that context for the decision. That makes them two sides of the same coin; equally important. As a general framework to abstract executable decision from a manual process, I would firstly start at the process side of things, one could call this a process, what are we actually doing, and again, you can still do that with your clipboard and your timer. Just trying to observe what the process is. This gets more difficult in financial organizations where you cannot really observe it, because it is all in systems and it is all semi-automated. But there is some discovery element in it. Secondly in this process, I would try to find my decision points and actually you could do that on a high level, you do not necessarily need to iron out all the details of decisions right away, because then you can focus sort of doing breadth first, instead of depth first. Figure out what the process is and where different decisions are and then defining them. Once you sort of have that on a high level, process and decisions together, I would start, I would focus on the decisions first, instead of ironing out all the details of the process. There is a lot of information in the decisions that will inform you how your process could be optimized or run in a better manner. My third step would be to define the decision criteria, define how this decision is made up. Determine discount, OK, what kind of criteria am I looking at? Do I look at the age, do I look at the length, the duration of the account, and is it a long standing client or not? Will I look at the citizen status, is it a senior	DAN RDY

		citizen or a veteran. What are the criteria or conditions I want to find and apply on a certain decision? And then fourthly I would look at the requirements of a decision. Ultimately my goal was automation, one way to automate is satisfied with data, and there is a single simple object in a DMN notation for that. So, what is my input data, what data am I trying to work with? That is a whole, sometimes it is a whole phase in the project itself, because it is so complicated where data and different data layers come from and often you have complexity in data when you have to aggregate. I want to see how profitable the client is to determine the discount, that means I have to look at all those orders, I have aggregate all these different account that a client has with me. That means I have to aggregate account information in order to see how profitable the client really was. There is a lot of complexity there that could improve or make your decision more complicated. So define the data which comes in that fourth step and then fifth is going back to the process, that connecting step to process. Which is defining the conclusion of the outcome. So, if defined what a decision was and then look what it can do with that decision, but now what needs to go back into the process to figure out what the next step is in the sequence. Will I fire off another decision? Will I store something, is there a manual step after this decision? Maybe the user, who can read the screen, is validating something or is clicking approve. So what then is my next step? What is my outcome to form my next step? I would roughly iterate over this five-step-framework.	
29.	TB	Okay, and in step four, you were talking about the input data of a decision, but this could also be another decision, right? Functioning as input data? Or does it not work like that?	
30.	P4	That is a good question. When I am talking about input data, I am talking about raw data that is put in. So, someone's name is less relevant for a particular decision, unless you want to discriminate on names somehow. But other raw data or data that you sort of constructed for the particular purpose of the decision, that is probably what you are pointing towards. You pass that in as well, but to zoom in that what you are talking about, constructing particular data specific for a decision. I have sometimes done that, sometimes applied particular sourcing strategies in order to aggregate or collect a piece of data in order to make a decision smarter or better or more accurate. But that is not a decision in itself, but that could also	DAN

		become a more philosophe debate. Even if it is reference data or extracted data can be passed in.	
31.	DB	Okay.	
32.	TB	Alright, then we move on, what techniques re used to automate a decision? Or to create a decision service?	
33.	P4	A number of different techniques exist. Looking at the sort of decision service platform that we used in the organization I was part of. First of all there is a rule engine that executes automatically, which implies that the model we have built is transformed into code and then readable for a particular engine, in the case the rule engine. So, that remains at the core. There are a number of them out there, some open source and some paid for. All the big players pretty much have one. Around that core, there were a number of different other components in order to supplement the platform that we had. One of the components was an analytical component, the component functioned as a storage, as a capture and as an entry point for people to look at. What did the execution do? What is the execution path? The different rules throughout the decision three? Was the performance of this decision right? Did it take two seconds or two hundreds of a millisecond to execute this decision? What was the raw data that was passed in? Especially, if you have an STP, straight through process, where there is not really any data check. You just pull in data from a system, running it through the system and then validate the outcome. It that case, there is no real validation of what is going into the decision, is that really clean? High quality data? So there is an analytical component on it, obviously because it is a decision service, there is a whole SOA architecture around it. Which meant different sorts of API's, API's that could manage large transactions, it was not like: here is one transaction, give me the conclusion, but here are two million records, give me all the conclusions in a particular order. There are different API's to connect into that whole architecture. Additionally, there was continuous improvement of that, especially around performance, a lot of the times, especially financial industries, who have millions and millions of transactions to do, especially if you have business logic on a single transaction, it becomes quite difficult for a small rules engine to coop with it. There was a lot of optimization done in it to increase and when it comes down to hardware, you can increase the server park. Create virtual server to spread the	DAN AUT REL:DAAN

		load, load balancing. But that automatically came back to how we modelled something. There were particular models that were badly modelled, that would reduce your speed. There were particular decision constructs that we used, but you have to trade that of with speed or latency. So, this was an interesting space where we had to watch how the technology involved and how we then modelled it and built it in a way that was good.	
34.	TB	Okay, and all those components you just mentioned, are they part of a Business Rules Management System? A BRMS?	
35.	P4	This was in-house built. So we took the rules engine and built the components around it. Because the need for a service. I hope that other business rules management software vendors provide all these components, because I think that they are vital to, again, improve your decision execution, and improve the technical side of decision management. Over the top of my head, I am not sure if every BRMS does provide this. But a part of this was in-house built and a collection of open source functions.	DMT DAN AUT
36.	TB	Okay, next question. I believe you have already mentioned something about it. After the rules are made and the decision are automated, who is going to maintain those decisions, the automated decisions?	
37.	P4	Yeah, very good question and I think that is a question I seek to answer in every project. The answer really is, it differs per project. We have not manage to find a single one fitting solution for all projects. This is how decision management maintenance is going to happen, this is the role of a maintenance modeler, this is exactly the steps he can do and this is all what he cannot and can do. So it differs per project, but then what is the difference, what is the distinction. First and foremost I think the context, sometimes you have a context where it is quite easy to teach a business user to maintain a particular set of rules or given the opportunity to give him access to his own systems. Not every context has that option. Often that also depend on the people you are working with, some are technical, some have a function that borders a technical world, for example we had a reference data business team, they were on the business side because, and they understood the data. And there was a lot of business context to the data. They were technical in themselves, they had skill sets	DMT MAI MOD

		in order to do programming and logical thinking. This is where it becomes quite easy for them to teach them DMN and show them a notation they understand. But if you have a real hardcore trading function, people have a business mindset, they have business processes in mind, they understand how to sell, they understand how to market a particular products, and they have those skills. Then it becomes difficult to maybe teach them DMN, even though it's easy, even though it is a language that is understandable, they do not really want to have that responsibility. They still have more of a traditional [roles and responsibility] mindsets, you see that natural pushback from people. Saying: Wait, this has historically seen not be my role, why is it suddenly my role? I am not really interested in changing this or have the information to do this. That is where IT becomes people management and ultimately a people problem and not necessarily an IT problem. Between those ranges we had different projects sometimes. If you had a real business unit that was core business, you had a support team that was still on the business side but they could maintain the business process and responsible for the business processes. They were Subject Matter Expert in the process and they were sort of stepping away from the real business and they were becoming more managers. In those cases, we sometimes had manager looking after ownership of particular decision models. And another case, which was more in the middle [of this range], in the organization I was part of, there was a big change organization that was responsible for business change going on in the organization. Even at times they took on the responsibility to maintain the models, because obviously I was part of that organization we taught people the ins and outs of decision management and how to model and how to maintain and to understand all the risks. They were supporting particular projects, sometimes over time they did all the maintenance, changes went in and this way they prevented high level incidents were we could lose a lot of money. The second part of this question is I think the business case. Ultimately you go into a business unit you want to change something, but what is your business case for maybe decision management? That is why we tried to teach our capability managers to start thinking about maintenance, even before project is started. It is often that this is sort of an afterthought, let build it first and then we will see how to maintain it. You sort of have to make the case for the maintenance as well. What is the organization like? What are the skills people have that we work with? And what does that	

		mean, what are the different options for the maintenance of your decision?	
38.	TB	Alright, good example.	
39.	DB	Yeah, very clear. Alright, so if we move on, to the next part, the analytics part. In your opinion, how does analytics add value to such automating decisions? Or what is the influences of analytics in such automated decision making?	
40.	P4	There is a ton of influence. I think that first and foremost is something we have not necessarily worked a lot, but I like to work on in the future. This was not a particular project, but I think one example is the concept of smart decision, right? In the organization I was in, we often poured in data, made a particular decision and we went on our way. But what if that data, or the collection of that data is smarter or is based on more statistical calculations or machine learning algorithms that run through the data spotting patterns and then raise it to a particular business decision. So the concept of smart decisions in the industry you hear, I think this is the connection of BI and decision management. This is I think definitely a big influence and that is where it will probably go to anyway. Especially, because a lot of IT systems, the IT landscape is also evolving, we almost need to go there, these sort of dumb decision that are acting on a single piece of data, that will probably in the future be something of the past.	ANS REL:DMAN
41.	DB	Right.	
42.	P4	Secondly, in the organization that I was part of, we applied a lot of the analytics on the decision execution. I think I highlighted it in another question. Often using it for debug purposes, so to understand what happened in the decision, but also for monitor purposes. We build a dashboard afterwards, to allow business user to see sort of the volume that they were dealing with, if there were any particular peaks. So then they could make sort of strategical decisions, add particular resources here or focus on a particular product more. Almost, your typical BI case, like where your product is sold a lot, we need to stack up inventory and need to make sure inventory is updated. Giving them [business users] controls like that, this is where BI and BDM very much come together, because you need your BI thinking and your BI theories around dash boarding in order to sort of build dashboard that makes sense	ANS MAI REL:DMAN

		from a decision management perspective. What do you really want to see on this dashboard that will support a decision? What will make you act in a particular different way, if you see this dial going to the red? So there was a small project where we have done this, bring in your BI specialist to help formulate this kind of plan and formulate the solution.	
43.	DB	Yeah, right. Interesting, so it is used a lot for maintaining and monitoring, but to what extent is it used to originally design such decision services?	
44.	P4	Yes, very good question and I think I should definitely add that here. It has been used depending on the project. Sometimes the project took time to look at historical data and figure out what depends are and what the actual knowledge should be and sometimes business knowledge is actually in your data and the rules that you want to define is ultimately extracted from the data that you working with. Percentage wise, this is only five percent of the projects. Often times, people have the business knowledge in their head or it is written in a policy. So that is on the majority of projects I have worked on, but on a small number, we did do things like that. It sort of borders optimization as well, if you have a simple policy based rule, even if you simply look at a simple rule over time, you could still have to update it and review how to optimize this decision. It is often a timing thing, right? In the first case, the case that you were talking about, you do that to initiate the rules, to define an initial set. And later on you apply the same functions and basically sometimes the same sourcing techniques in order to optimize the decision and figure out how it [rules] should be improved or how it should change.	ANS RDY
45.	DB	So it is part of the original design, but more so for the maintenance and optimization of such decision services?	
46.	P4	Exactly.	
47.	DB	Right. In your opinion, how will it develop in the future? The use of analytics in the BDM process and the automating decision making?	
48.	P4	I hope it will more evolve towards the analytical part. So where we really start connecting machine learning and the optimization algorithms with the decision making. It is a very interesting one, because, ultimately one could argue, well if	DAN ANS

		you can extract your rules from a lot of data that you have, what is the need for DMN as a notation? One could answer, that is just to visualize or to have a common language when the business runs it. But definitely we need that strict connection, because otherwise they become relatively dumb rules and decisions. And ultimately machine learning started with rule based pattern recognition, right? If you have a person that is 25 years old and it is in the afternoon and he is visiting a supermarket and it is a Thursday, then he is probably going to buy beer. That is a very simple rule that is extracted some time ago. But we cannot continue to build simple rules that say he is a man, it is now five o'clock on a Thursday, we are offering beer. So we need to be smarter and I hope it will evolve that way.	
49.	TB	Interesting.	
50.	DB	Yeah, definitely.	
51.	DB	Do you have anything more to add on or any comments on the context of decision management or decision automation? In relation to analytics?	
52.	P4	Definitely as a concluding comment, bear in mind that DMN is obliviously a relatively young notation. BPMN took a couple of version for people to really start using it and for it to become a standard across the industry. So that is one thing to keep in mind, sometimes we want to go really fast and forget for new things to improve the notation. For future improvements, I think to keep in mind is that we need to get the true value proposition. Even if you look at the value propositions that you guys listed in the intro PDF, a lot of values defined there are values applied generally if you automate something. If I program something in Python, I will probably get more accuracy and better decision making even though it is not really a DMN decision or if I teach a person or a dog to do something. The true value proposition you sometimes hear from the likes of James Taylor on a theoretical level are not truly value propositions or added value in an organization. Especially, where you have a big organization with a big IT. The department that says: we can program anything, we can build anything, the fanciest algorithms from the open source community, and we can apply it in any shape or form you want, just tell me what to do. And that is often where it goes wrong. Tell me what to do, well we do not really	DAN DMT DMV

		no how to tell you what to do, so that is where the whole problem sits. The point being that, in order to convince an organization, especially technologist, about using and applying decision management, it really need to define clearly what that benefit is, how that will benefit them and the business. That goes beyond, it improves accuracy and consistency. Transparency is out of that list, I will keep transparency because it is not a common language, not everybody speaks programming and DMN is a simple notation, so transparency is definitely on added value list, but we need to define more and that will probably come over time, when the notation matures.	
53.	DB	Right.	
54.	P4	Sorry, and lastly I think that will come back to business empowerment as well, right? As soon as we, and that is often a pattern that we see in projects, that we can convince the technologist that this is a good idea and he agrees with your value-add. Then it becomes a sort of a people management issue on the business side. How do we empower them, how do we convince them that really empowers them be agile and to be quick and to reduce costs, etcetera? Because in business empowerment, the point of discussion is that it is completely new for a lot of businesses to really control their systems. And often times in big organizations, especially banks, it is quite a big change for them to be responsible for executable code, for their systems and how their systems behave. So we need to keep that in mind when DMN matures as well as, and to ensure the industry to have the right guidelines to create a controlled environment that can be applied. Because otherwise we fall for the same trap as BPMN, where someone once said, we can do executable BPMN and all the IT people laughed and said: no no no, we are never going to give executable power to any business stakeholder and obviously this is what we are now doing DMN. To prevent that pitfall, we need to set the guidelines and the best practices and industry wide forms around it.	DMT MOD
55.	DB	Right, awesome.	
56.	P4	I hope that does make sense.	
56.	TB	Yes.	

57.	DB	Yes, it is very clear, a good explanation.	
58.	TB	The examples are very interesting.	
59.	DB	Then I will close the interview and want to thank you for your participation, it was very insightful and thank you very much.	
60.	P4	You are very welcome.	